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# **Why do we want to defer actions on climate change? A psychological perspective**

A Thesis

Submitted in partial fulfillment of the requirements for

the degree of

Doctor of Philosophy

in

Engineering and Public Policy

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## **Abstract**

A 2007 U.N. survey found that 54% of Americans advocate “wait-and-see” behavior on policies that mitigate climate change, i.e., they infer that climate mitigation actions can be deferred until there are clear signs of danger. By evaluating different cognitive factors that influence human behavior, this thesis builds a framework that provides answers to an important question: why do people advocate wait-and-see behavior on climate change? One cognitive factor is misperceptions of feedback (i.e., ignorance of large feedback delays between CO<sub>2</sub> emission decisions and the corresponding changes in CO<sub>2</sub> concentration). Results reveal that the use of simulation tools, that provide repeated feedback about decision actions and corresponding consequences, is likely to enable people to overcome these misperceptions. A second factor is people’s reliance on correlational or linear thinking (that the shape of CO<sub>2</sub> emissions and CO<sub>2</sub> concentration should look alike). Results reveal that the use of a physical representation (i.e., a picture of a problem in the form of a metaphor), simulation tools, and presenting problems such people’s reliance on heuristics and biases enables them to make ecofriendly decisions is likely to enable people to overcome their correlational thinking. Other cognitive factors that affect people’s wait-and-see behavior include people’s risk and time preferences about future climate consequences when these consequences are either described or experienced. Results reveal that descriptive methods (e.g., books, newspapers, and reports) are likely to produce more wait-and-see behavior due to a high probability, small cost, and late timing of future consequences; whereas, experiential methods (e.g., movies, imagery, and games) are likely to produce more wait-and-see behavior due to a low probability, large cost, and early timing of future consequences. Policy implications suggest a careful design of descriptive and experiential

climate risk communication methods, and the use of above described manipulations to improve people's decision making on climate change.

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# Chapter 1: Introduction and Motivation

## 1.1 Introduction

Despite strong scientific consensus about causes and risks of climate change, the general public seems to exhibit a complacent attitude towards actions that benefit Earth's climate (Bostrom et al., 1994; Leiserowitz, 2007; Read et al., 1994; Weber, 2006). Recent surveys have shown that most Americans exhibit “wait-and-see” behavior, according to which they infer that mitigation actions on climate change (e.g., reductions in yearly greenhouse gas (GHG) emissions) can be deferred until there is greater evidence that climate change is harmful (Sterman & Booth Sweeney, 2002, 2007; Leiserowitz, 2007). People's wait-and-see behavior on climate policies is currently widespread. For example, a 2007 U.N. survey found a large majority of U.S. respondents (54%) advocating a wait-and-see or go-slow approach to emission reductions (Sterman, 2008; Leiserowitz, 2007), and larger majorities favoring the wait-and-see option in Russia, China, and India (Sterman, 2008; Leiserowitz, 2007).

Moreover, recent evidence shows that wait-and-see behavior is also widespread among policymakers who directly decide on policies that mitigate climate change. For example, Tony Abbott, opposition frontbencher and a senior member of the Liberal Party of Australia in response to a news-poll commented, “The government should not be rushing headlong into any premature trading scheme [for policies that mitigate climate change]” (Conway, 2009, para. 2). Also, the former White House science adviser John Marburger briefed a Senate Panel on climate change, saying, “We know we have to make very large changes *if* this [climate] turns out to be a problem. The consequences of human-induced global warming could be quite severe” (Jones, 2002, para. 2). At the

same briefing, the U.S. administration stood behind its wait-and-see behavior by claiming that, “we should only slow the growth of greenhouse gas emissions (GHGs), and - as the science justifies - stop, and then reverse that growth” (Jones, 2002, para. 3). Similarly, Fred Singer, professor emeritus environment sciences, University of Virginia, expressed a stronger wait-and-see view by commenting that, “human activities are not influencing the global climate in a perceptible way. Climate will continue to change, as it always has in the past, warming and cooling on different time scales and for different reasons, regardless of any human action” (Singer, 2009, p. 1).

Amidst these wait-and-see statements, there is a growing consensus that Earth’s climate is likely changing as a direct result of human actions such as burning of fossil fuels and deforestation that lead to greenhouse gas emissions (IPCC, 2007a; Arctic Climate Impact Assessment, 2004). Although there are serious concerns for Earth’s climate among certain climate scientists, citizens, policymakers, and governmental officials, it is clear that a majority of people currently prefer to exhibit a risk-seeking wait-and-see behavior on initiating any actions that mitigate climate change.<sup>1</sup> People’s wait-and-see behavior is risk-seeking because holding off actions that mitigate climate change is likely to invite climate “black swans” in the future, i.e., high-impact, hard-to-predict, and rare climate consequences beyond the realm of normal expectations (Taleb, 2007). That is because, unlike simple systems that have short delays between detection of a problem and the implementation of corrective actions (e.g., boiling beans in a cooker where upon hearing the whistle one could immediately remove the cooker from the

---

<sup>1</sup> Defined more formally, consider these two choices: A. Paying a certain amount now for sure and reducing the future impacts of climate change; or, B. Defer paying now and paying a larger but an uncertain amount in the future as a result of climate change. Then, a choice for option B is a measure of risk-seeking behavior on climate change. This risk-seeking choice also exhibits wait-and-see behavior to climate change mitigation actions in the status quo.

flame), for a complex system like Earth's climate there are long delays between the decision to mitigate emissions and the corresponding changes in atmospheric greenhouse gas (GHG) concentrations (IPCC, 2007b; Sterman & Booth Sweeney, 2002, 2007; Sterman, 2008). Therefore, for the climate change problem, one cannot afford to delay acting (i.e., exhibit wait-and-see behavior) till the last day and then decide to take actions when there are clear signs of danger due to climate change. On account of deferring immediate mitigation actions and the long feedback delays in the climate system, the climate black swans experienced in the future are likely to be negative consequences in the form of severe storms, sudden melting of polar ice-caps and droughts that occur in different parts of the world. Also, the cost of adaptation to these negative consequences is estimated to be very large (IPCC, 2007a; Nordhaus, 1994).

Currently, there is lot of technological and engineering research on developing mitigation options for climate change. Some of these technological options include carbon capture and sequestration (CCS), geo-engineering, and switching to renewable sources of energy (IPCC, 2007a). This technological and engineering research is very important and very much needed. However, as the decisions to adopt different technological and engineering options ultimately rests with people, therefore, research that studies the role of people, their understanding of climate change, and their wait-and-see behavior on climate change is also critically needed, though currently lacking in the literature (APA, 2009).

This thesis fills this void and directly considers the role of people, their wait-and-see behavior, and their understanding of climate change. In order to explain people's wait-and-see behavior, this thesis takes an approach that is different from applying

standard economic methods like cost-benefit analysis, where one would justify people's wait-and-see behavior in terms of sure costs now versus larger and uncertain costs of consequences that are distant in the future and that are discounted at high discount rates (Monbiot, 2009; Nordhaus, 2008; Stern, 2006).<sup>2</sup> Rather, this thesis proposes a framework of people's wait-and-see behavior by considering different cognitive factors that are peculiar to how humans make day-to-day decisions. Therefore, this thesis considers the human perceptions and decisions on climate change from a cognitive perspective. Given that climate change is already occurring in some parts of the world while people continue to exhibit wait-and-see behavior on the problem (Arctic Climate Impact Assessment, 2004), the main purpose of this thesis is to investigate from a cognitive perspective the following research questions:

Q1: Why do people want to defer mitigation actions on climate change when science currently shows signs of a rapid change in Earth's climate?

Q2: Furthermore, is there a way to influence people's wait-and-see behavior through certain manipulations?

Different chapters in this thesis investigate both these research questions using an experimental laboratory-based approach. This approach involves systematically

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<sup>2</sup> Discount rate is the rate at which a future cost (F) is discounted to the present cost (P). The exact relationship is  $F = P * (1 + i/100)^n$ , where  $i$  is the per annum discount rate and  $n$  is the number of years in the future after which cost F is incurred. If future costs of climate consequences is large, then even for a moderate discount rate (~ 8%), the calculated present costs will be very small. From an economic perspective, these costs of future consequences in the status quo will be small and this observation is likely to make people exhibit wait-and-see behavior on policies that mitigate climate change.

manipulating certain conditions and collecting behavioral data, where human participants make judgment and choices on climate problems in a controlled laboratory environment.

## **1.2 Background and Contributions**

There could be several potential reasons for people's wait-and-see behavior on climate change. Recent research has concentrated on the effects of the current costs of mitigation actions (using a high discount rate for future costs) and denial, i.e., ignorance of the climate change problem (Monbiot, 2009; Nordhaus, 2008; Stern, 2006). These economic reasons on cost and benefits have been the topic of many current investigations.

Furthermore, there is also research that has considered the role of motivational factors on environmental decisions (e.g., political ideology, perceptions of needs versus luxuries, and core psychological needs etc.) (APA, 2009; Hardisty, Johnson, & Weber, in press). For example, in November, 2008 there were devastating fires in southern California disrupting the ecology of that place; however, very few people (including those that had lost houses in the previous fires) decided to move out of the region. One motivational factor that explains this behavior could be place attachment (Gifford, 2007), i.e., continued attachment to family, job, and community, a motivation that can be more salient in the aftermath of adverse events, when fears have faded, than the goal of avoiding a low-probability future disaster. More recently, in other but similar situations involving organ donations (Johnson & Goldstein, 2003) and insurance decisions (Johnson, Hershey, Meszaros, & Kunreuther, 1993), the role of cognitive factors like status quo bias and inertia have been documented as reasons rather than the motivational

factors. As there is evidence in favor of both cognitive and motivational factors, they are both likely to influence people's decisions on environmental problems.

In this regard, although the role of motivational and economic factors in connection to environmental problems is documented in literature, the role of cognitive factors has been somewhat less studied and downplayed (APA, 2009). Due to the inseparable interaction of humans' actions on climate, it is important to investigate the role of certain cognitive factors that are likely to influence people's wait-and-see behavior on climate change. Detailed below are some of the cognitive factors and how this thesis builds upon these factors to suggest a framework of people's wait-and-see behavior.

### **1.2.1 Misperceptions of Feedback**

According to the misperceptions of feedback (MOF) hypothesis (Sterman 1989), people ignore the feedback delays present in their decisions in a dynamic system. In the case of the Earth's climate, the MOF hypothesis suggests that people are likely to fail to take into account the long time delays between increases in carbon-dioxide (CO<sub>2</sub>) emissions and the subsequent increases in CO<sub>2</sub> concentration, and the delays between increases in CO<sub>2</sub> concentration and its effects on increasing average atmospheric temperature (Sterman & Booth Sweeney 2002; 2007). In Earth's climate, an increase in CO<sub>2</sub> emissions does not increase CO<sub>2</sub> concentration and atmospheric temperature immediately, but after a long delay where it might be too late to act to avoid significant impact of these increases.

Moxnes and Sagsel (2009) have built on Sterman and Booth Sweeney's (2007) results by focusing on how people incorporate feedback delays in their decisions and

regulate CO<sub>2</sub> emissions in order to reach an attainable CO<sub>2</sub> concentration goal in a simulated climate system. They tested participants' ability to control CO<sub>2</sub> concentration to 300 GtC above the pre-industrial level in a period between the years 2000 and 2100, where participants decided on emissions every 10 years. They tested participants in different conditions that mimicked the working of the climate system, with repeated feedback about decisions and the resulting changes in CO<sub>2</sub> concentration. Participants entered ten numbers which represented their emission decisions every ten years over a 100 year period. In all but one feedback condition, participants entered *all* ten emission values at one time and then observed the effects of their decisions on the CO<sub>2</sub> concentration over the 100 year period. In conditions without feedback, Moxnes and Saysel's (2009) results coincided with results from Sterman and Sweeney (2007): Participants showed a general tendency to overshoot the goal level, misperceiving feedback delays in their emission decisions. In the feedback condition, however, Moxnes and Saysel (2009) gave participants the ability to make repeated emission decisions every 10 years and to observe the effects of these decisions on the CO<sub>2</sub> concentration before the next 10 yearly emission decision was made. Within a 10 year period, the emissions remained constant at values which were set at the start of the period. Results show that providing repeated feedback helped participants change their strategy over time, and may have helped them to reduce their misperceptions of feedback delays.

In this thesis' chapter 2, Dutt and Gonzalez (2009) extend results of Moxnes and Saysel (2009) and Sterman and Booth Sweeney (2002; 2007) in a task called the Dynamic Climate Change Simulation (DCCS),<sup>3</sup> where participants control CO<sub>2</sub>

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<sup>3</sup> The DCCS simulation can be downloaded for free under an academic license from: [http://downloads.ddmlab.com/?action=form&package\\_id=2](http://downloads.ddmlab.com/?action=form&package_id=2)

concentration to a goal level under different kinds of feedback delays in inputs (CO<sub>2</sub> emissions) and outputs (CO<sub>2</sub> absorptions). The design of DCCS has been motivated from a generic dynamics stocks and flows task (Gonzalez & Dutt, 2011) and the use of the “bathtub metaphor,” where CO<sub>2</sub> emission is represented by a tap, CO<sub>2</sub> absorption is represented by a drain, CO<sub>2</sub> concentration is represented by the amount of liquid in the tub, and the tub itself represents Earth’s atmosphere.

Using DCCS in an laboratory experiment, Dutt and Gonzalez (2011) have systematically varied two types of feedback delays in DCCS, the frequency of making emission decisions (frequently or infrequently) and rates of CO<sub>2</sub> absorption (rapid or slow). They show that when laypeople are presented with the problem of controlling carbon-dioxide (CO<sub>2</sub>) concentration in DCCS, people who perform in realistic climate conditions (where the rate of CO<sub>2</sub> absorption is slow and emission decisions are made infrequently) produce larger CO<sub>2</sub> emissions compared to people who perform in more optimistic conditions (where the rate of CO<sub>2</sub> absorption are fast and emission decisions are made frequently). These results are explained by the difficulty individuals have in perceiving feedback delays in dynamic systems (Diehl & Sterman, 1995; Booth Sweeney & Sterman, 2000; Sterman & Booth Sweeney, 2007; Sterman, 1989; Sterman, 2000; Sterman, 2002; Sterman, 2008). According to Dutt and Gonzalez (2011), people in conditions of feedback delay exhibit wait-and-behavior in their yearly CO<sub>2</sub> emission policies because people continue to maintain their emissions at a high value (as is the case in the world presently) and when they want to cut the emission to meet absorption upon hitting the goal (which is needed) it becomes too late for them to act. Here, cutting down emission to meet absorption is something that opposes people’s wait-and-see

behavior and is needed right from the start in the task, rather than only upon reaching the goal. However, results also show that participants do learn to improve their emission decisions by cutting down emissions over many repeated trials of decision making in DCCS. Thus, one manipulation for reducing people's misperceptions of feedback delays, that this thesis proposes, is the use simulation tools like DCCS that compress time and space and that improve people's understanding of the dynamics of Earth's climate over repeated interactions with these tools.

### **1.2.2 Reliance on Correlation Heuristic**

In addition to the human misperceptions of feedback delays (Dutt & Gonzalez, 2011; Sterman, 1989), a less explored cognitive factor for people's wait-and-see behavior is the human tendency to rely on "correlation heuristic" while making judgments about a level or accumulation (e.g., CO<sub>2</sub> concentration in the atmosphere) based on CO<sub>2</sub> emission (inflow) and absorption (outflow), respectively (Cronin & Gonzalez, 2007; Cronin, Gonzalez & Sterman, 2009).<sup>4</sup> According to correlation heuristic, people incorrectly assume that the shapes of accumulation and inflow overtime should be identical. For example, it has been shown that highly educated people rely on correlational thinking, assuming that if the task demands one to increase the GHG concentration to stabilize at a higher level than the status quo, then GHG emissions should also increase and stabilize in an identical manner to the GHG concentration (Sterman & Booth Sweeney, 2002; Sterman & Booth Sweeney, 2007). People's reliance on correlation heuristic for Earth's climate supports wait-and-see behavior and violates basic laws of physics. That is

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<sup>4</sup> Inflow and Outflows are rates of change and the change in accumulation is the integral of the difference between the inflow and outflow. Therefore,  $Accumulation(t) = \int_1^t [Inflow(t) - outflow(t)] . dt + Accumulation(0)$ .

because, for Earth's climate, the CO<sub>2</sub> concentration has been increasing nonlinearly over time (years) due to an approximate linear increase in CO<sub>2</sub> emissions every year (IPCC, 2007). By relying on correlation heuristic, people are likely to judge the nonlinear CO<sub>2</sub> concentration's shape to be linearly increasing over time, i.e., similar to the linearly increasing shape of CO<sub>2</sub> emissions. Consequently, such linear judgments are likely to make people underestimate the actual nonlinear increase in CO<sub>2</sub> concentration, undermine the seriousness of the climate problem, and make them exhibit wait-and-see behavior.

As reliance on correlation heuristic is likely to be very problematic for immediate actions on climate change, this thesis investigates a number of manipulations that aim to reduce people's reliance on this heuristic and the associated misconceptions. One of the manipulations relies on using DCCS among people from both the science and mathematics backgrounds (STEM) as well as the humanities and arts backgrounds (non-STEM) (Dutt & Gonzalez, 2011a) (chapter 3). Dutt and Gonzalez (2011a) put participants from both STEM and non-STEM backgrounds in two separate conditions in a laboratory experiment. In one (control) condition, participants sketched the CO<sub>2</sub> emission and absorption trajectories they thought to correspond to a given CO<sub>2</sub> concentration stabilization (CS) scenario over 100 years on a sheet of paper (i.e., the CS Task, Sterman, 2008). In a separate (experimental) condition, participants controlled the CO<sub>2</sub> concentration as close as possible to a CO<sub>2</sub> stabilization trajectory (same as that given in CS task) by indirectly manipulating the CO<sub>2</sub> emissions and absorptions in DCCS over 100 years. Participants' performance in DCCS was followed by their performance in the CS task. Results revealed that the DCCS manipulation worked effectively in reducing

participants' reliance on correlation heuristic among both STEMs and non-STEMs in the CS task after performing in DCCS compared to when participants performed in the CS task alone. However, the benefits of DCCS performance were greater for STEMs compared to non-STEMs: the reduction in reliance on correlation heuristic was greater for STEMs compared to non-STEMs in the CS task after performing in the DCCS. One explanation of this observation is that previous exposure to mass balance and energy balance concepts in mathematics, science, and engineering enables STEMs to improve their sketches in the CS task because they focus less on the surface (i.e., irrelevant) features of decision problems, and focus more on the more fundamental underlying structure of the problem (Chi, Feltovich, & Glaser, 1981; Gonzalez & Wong, in press).

Furthermore, in chapter 4, Dutt and Gonzalez (2011b) hypothesize that people's reliance on correlation heuristic and their consequent underestimation of nonlinear accumulation are influenced by the format in which these problems are presented to them. Here, Dutt and Gonzalez (2011b) motivate and investigate the use of a physical representation to communicate climate problems as an alternative to other conventionally used representations that include text descriptions and mathematical graphs. Physical representation presents a problem using a picture that works as a "metaphor." For example, consider a mathematical problem where the length ( $L$ ) of a square's side is doubled and one needs to calculate the new area. A physical representation of the problem will be one where a single square tile of side  $L$  is replaced by four square tiles, each of side  $L$  (i.e., to form a square of side  $2L$ ) in a picture. In a series of experiments, Dutt and Gonzalez (2011b) have shown that the physical representation reduces people's reliance on correlation heuristic and their underestimation of  $\text{CO}_2$  accumulation when the

representation's use is compared to other graphical and text representations in different problems and contexts (that are even different from the climate context).

Finally, in chapter 5 and 6, Dutt and Gonzalez (2011c; 2011d) discuss an information presentation manipulation that is hypothesized to enable people to improve their decisions by directly relying on the correlation heuristic rather than reducing this reliance. According to the information presentation manipulation, one method of improving people's decisions is to present ecofriendly options in such a manner that these options appear more attractive to people when they rely on linear thinking. Therefore, if people choose an ecofriendly option by relying on linear thinking, then they will pick an option that mitigates climate change without any alteration in their incorrect linear thought process. For example, in chapter 5, Dutt and Gonzalez (2011c) discuss how linear thinking could be particularly problematic in the case of interpreting carbon-dioxide's ( $\text{CO}_2$ ) lifetime in the Earth's atmosphere. They took participants from policy and non-policy backgrounds and asked them to rank five ranges of  $\text{CO}_2$  percentages to be removed from the atmosphere according to their impact on  $\text{CO}_2$ 's lifetime in two separate conditions: Aid and no-Aid. In the Aid condition, participants were provided with a descriptive decision aid through instructions that would likely enable them to answer the problem correctly, while this aid was absent in the no-Aid condition. Two problems were presented to each participant in random order: Linear, where a ranking based upon linear thinking yielded a correct rank order; and Nonlinear, where a ranking based upon linear thinking yielded an incorrect rank order. Results revealed that a majority of participants from both backgrounds responded linearly on both problems and got the problem correct where a linear response gave the correct answer. Furthermore, although the decision aid

had no effect on participants' correct responses, it enabled policy backgrounds to move away from responding according to linear thinking. In another example in chapter 6, Dutt and Gonzalez (2011d) have applied the same information presentation manipulation to ecological (eco) taxes, which are promising mechanisms to enable ecofriendly decisions; however, which do not currently enjoy popular public support. Dutt and Gonzalez (2011d), show that thinking linearly people rely on the linear-thinking heuristic, i.e., they prefer a small price increase while associate larger price increases to mean proportionally greater benefits or improvements in quality. Participants were asked to choose between two eco-tax increases in two decision problems: in one, the smaller eco-tax increase resulted in greater CO<sub>2</sub> emissions reduction, while in the other, the smaller increase resulted in lesser reduction. Although larger eco-tax increases did not always save more CO<sub>2</sub> emissions, a majority of participants preferred the smaller eco-tax increases, while judging larger tax increases to cause greater reductions in CO<sub>2</sub> emissions (i.e., they relied on the linear-thinking heuristic). Since participants rely on the linear-thinking heuristic in reaching their preferences and judgments about eco-taxes, eco-tax policies are likely to benefit by presenting information such that smaller tax increases (which are linearly more attractive and are likely to be chosen by people) cause greater CO<sub>2</sub> emissions reductions.

In the different manipulations discussed above, the approach taken is either to help people reduce their reliance on the discussed cognitive factors, or to use that very reliance to promote decisions that mitigates climate change.

### **1.2.3 Risk and Time Preferences**

Another cognitive factor for people's wait-and-see behavior is related to human risk preferences, i.e., people's risk-seeking (wait-and-see) or risk-averse (act-now)

behavior when they make choices based upon either reading a written description of the likelihood and outcomes or after an actual experience of the frequency and outcomes (Hertwig et al., 2004; Hertwig, 2009; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Research has shown that people underweight rare events when they experience the small frequency of occurrence of these events; whereas, people overweight the same rare events when they read written descriptions about these events and their likelihood of occurrence (Hertwig et al., 2004; Hertwig, 2009). For Earth's climate, although there are many available written descriptions that detail the future likelihood and consequences of climate change (e.g., newspaper, climate reports, and books etc.) (IPCC, 2007a; IPCC 2007b; Gray, 2009; Sterman & Booth Sweeney, 2007; Sterman, 2008), people's every day experiences of climate change may be very different from what these descriptions suggest. For example, it may be very difficult to currently detect changes in Earth's climate in people's everyday experiences, because these changes are very gradual and slow for human perception to notice; therefore, the associated consequences might be perceived as occurring with a low probability (i.e., rare events). As people underweight rare events in experience (Hertwig et al., 2004), their perceptions of these rare climate consequences is likely to be low and consequently people will exhibit wait-and-see behavior on climate change. However, climate scientists, who primarily rely on written descriptive knowledge about climate change rather than their experiential knowledge of climate change, are likely to overweight the same rare events and promote immediate actions on policies that mitigate climate change.

In addition to people's risk preferences due to probability of consequences, people's time preferences also seem to impact their wait-and-see choices. There is

currently uncertainty about when or how soon climate consequences are expected to appear (Nordhaus, 1994; Öncüler, 2010). According to literature on inter-temporal choice, people's repeated choices for risky and safe options in both experience and description under a time delay depend on whether the delay provides an incentive (Luhmann, Chun, Yi, Lee, & Wang, 2008; Wu, 1999). Therefore, people are likely to choose a risky wait-and-see option, which produces a time delay between making a choice and observing the corresponding consequence, so long as people could derive an incentive during the waiting time. For climate, if negative climate consequences occur early in the future (e.g., 10 years from now), then the cost of consequences may outweigh the economic gains that people make while waiting for a short time. However, if these climate consequences occur later in the future (e.g., 60 years from now), the economic gains people make while waiting may outweigh the associated costs of consequences. If people's time-preferences are driven by the option that provides them with a greater incentive in both experience and description (Dutt & Gonzalez, in press; Luhmann et al., 2008; Wu, 1999), then we expect a greater proportion of wait-and-see choices when climate consequences occur later rather than earlier in the future.

In this thesis' chapter 7, Dutt and Gonzalez (in press) test people's wait-and-see behavior on climate change due to the uncertainty in both the timing and probability of future consequences. In a laboratory experiment, they presented their participants with climate consequences as carbon-taxes in one of two forms: a written description, where the probability, consequence, and timing were explicitly provided; and experience, where the probability, consequence, and timing were sampled through unlabeled buttons and then a final choice was made. In both forms, participants were asked to choose between

two options, one act-now and the other, wait-and-see. Four problems were presented in each condition such that the probability of consequences on the wait-and-see option was high or low and the timing was early or late. Results indicated that the proportion of wait-and-see choices was greater in experience than description. Furthermore, in both experience and description, the proportion of wait-and-see choices was greater when the probability was low rather than high. The difference in the proportion of wait-and-see choices between the low and high probability was amplified in experience and attenuated in description. Finally, there was no difference in the proportion of wait-and-see choices when the timing of climate consequences was early rather than late in both experience and description. Interestingly, the timing did not have an influence on the proportion of wait-and-see choices. A likely reason for this observation appears to be the absence of any incentive when people waited in experience or read about the wait in description. In the real world, people are likely to generate monetary incentives (e.g., remuneration) due to productive work and investment in the time they decide to wait for actions on climate change. Thus, due to lack of incentives in the above study in wait-and-see option, the early or late costs were likely perceived as costing equally to people.

In order to address the above issue of a lack of incentive in the time people wait, in this thesis' chapter 8, Dutt and Gonzalez (2011e) report a separate study. The new study investigated how a written description or an actual experience of cost, timing, and probability of future climate consequences affected people's risky wait-and-see behavior on climate change, where now a wait-and-see choice produced a monetary incentive to participants depending upon the time they waited before the cost occurred. In a laboratory experiment, climate consequences as carbon-taxes were presented to participants in one

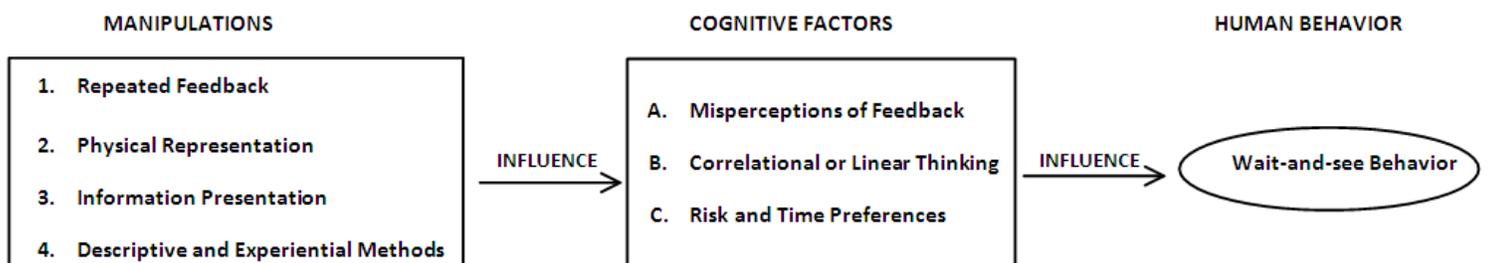
of two forms: a written description, where the cost, timing, and probability were explicitly provided; or experience, where the cost, timing, and probability were sampled through unlabeled buttons and then a final choice was made. Eight problems, each with an act-now (safe) option and a wait-and-see (risky) option, were presented in description and experience such that the probability of consequences on the wait-and-see option was low or high, the timing was early or late, and the cost was small or large. Results indicated that while in both experience and description, the proportion of wait-and-see choices was greater when the probability was low rather than high, the difference between low and high probability was amplified in experience and attenuated in description (replicating the findings by Dutt and Gonzalez, in press). Also, the proportion of wait-and-see choices was greater in description when the timing was late rather than early, and when the cost was small rather than large; however, the effects of timing and cost were absent in experience. In this study, unlike the study by Dutt and Gonzalez (in press), the timing of occurrences of consequences had an effect on people's wait-and-see choices in description and was as hypothesized: Greater proportion of wait-and-see choices when consequences occur later rather than earlier. Thus, providing incentives to people, during the time they waited for climate consequences to occur, seem to cause the timing to influence people's wait-and-see choices in description; however, not in experience.

In summary, this thesis theoretically motivates certain cognitive factors and manipulations that affect and influence people's wait-and-see behavior in a series of laboratory experiments. In the next section, these cognitive factors are brought together into a framework to explain people's wait-and-see behavior.

### 1.3 Significance

Although prior research has expounded economic reasons for people’s wait-and-see behavior on climate change, currently very little is known about how certain cognitive factors might influence this behavior. Considering the global nature of the climate problem and the associated large negative consequences in the future (IPCC, 2007a; 2007b; Sterman, 2008), the research described in this thesis contributes to certain cognitive factors that are likely to influence people’s wait-and-see behavior. This contribution is significant because no matter what technology or policy solutions are worked out for averting future climate change, these solutions will suffer from the problem of adoption and acceptance by the common and global populace without a proper understanding of how humans are likely to respond to these solutions and whether they are going to defer acting on these solutions (Sterman, 2008; APA, 2009).

Figure 1-1 presents a schematic diagram of how this thesis proposes a framework of people’s wait-and-see behavior by combining the role of different cognitive factors (described above) to influence this behavior. Furthermore, as shown in the figure, this thesis proposes a number of manipulations that influence people’s wait-and-see behavior through their cognitive factors.



**Figure 1-1. A framework about wait-and-see behavior as a consequence of a number of cognitive factors. Certain manipulations indirectly affect people’s wait-and-see through their cognitive factors.**

According to the research reported in this thesis, people's wait-and-see behavior on climate change is impacted by a number of cognitive factors listed in Figure 1-1. These factors include: people's linear perception of GHG accumulations in climate problems, their misperceptions of feedback delays present in different actions and consequences in these problems, and their risk and time preferences for uncertain future cost of consequences in these problems. Thus, according to this thesis, while designing technology or policy solutions for averting climate change, policymakers need to be careful and pay attention to the proposed cognitive factors that are likely to influence people's wait-and-see judgments and choices on these solutions.

Furthermore, as shown in Figure 1-1, this thesis provides a set of manipulations that indirectly influence people's wait-and-see behavior on climate change that is mediated through cognitive factors. One of these manipulations is to provide repeated feedback in simulation tools and in the real world after people make judgment and choices. Repeated feedback enables people to understand and observe the consequences of their decision actions and consequently correct their future decision actions. Another manipulation is to use the physical representation, i.e., to exhibit climate problems using pictures as metaphors that enable people to improve their understanding, reduce their misconceptions, and improve their decision judgments in these problems.

However, this thesis also argues that often times it might become difficult to change or alter people's reliance on cognitive factors, improve their decision making, and influence their wait-and-see behavior. Therefore, rather than change people's existing thinking processes, often times it might be beneficial to exploit these processes to enable

people to improve their decisions. As discussed above, according to the information presentation manipulation, presenting options that are better for Earth's climate as options that people are likely to choose due to their cognitive factors, will enable people to improve their decisions on climate change without any alteration in the way they decide on day-to-day problems.

Furthermore, this thesis also provides a theoretical account of people's wait-and-see behavior due to different forms of climate risk communication methods that are widely used: Some that are descriptive (newspaper and reports etc.) and some that are experiential (movies and simulations etc.). According to this thesis, people respond differently to the exact same information depending on whether this information is communicated using either experiential or descriptive methods of risk communication. Thus, this thesis provides important guidelines to policymakers on how to communicate information about magnitude of climate consequences, and their likelihoods and timing that manipulates people's wait-and-see behavior in different ways.

Finally, this thesis also contributes to furthering the study of cognitive factors. Therefore, this thesis extends what is currently known on how human behavior is impacted by different cognitive factors, namely, misperceptions of feedback, correlational or linear thinking, risk preferences, and time preferences. For example, currently little is known about how certain manipulations are likely to reduce people's reliance on correlational or linear thinking. This thesis suggests the use of repeated feedback and physical representation as two promising manipulations for reducing people's reliance on linear thinking. Similarly, people's time preferences and risk preferences have been studied as separate topics in abstract problems which have often

been disconnected from real-world problems like those concerning Earth's climate. First, this thesis takes into account both people's time and risk preferences together and analyzes their combined effect on people's wait-and-see behavior on climate change in the real world. Thus, the simple gambles used in this thesis' chapters 7 and 8 are both interspaced in time and probability and the results of their interaction extends understanding of human behavior due to both risk and time preferences. Second, the extension in this thesis that investigates the combined effects of probability and timing on human behavior is extremely relevant to the study of climate change. That is because, the climate change problem includes future cost consequences that are both uncertain in time and probability (i.e., when in the future and with what probability climate consequences are likely to be observed).

The upcoming chapters in this thesis systematically investigate the influence of different cognitive factors on people's wait-and-see behavior through a number of laboratory studies involving human participants.

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## **1.5 Next Chapter's Highlights**

The next chapter discusses the misperceptions of feedback hypothesis as a cognitive factor that influences people's wait-and-see behavior on climate change. An experiment is reported with DCCS, where different kinds of feedback delays in Earth's climate are manipulated. The effects of these manipulations are observed on people's ability to control CO<sub>2</sub> concentration to a goal level.

## **Chapter 2: Misperceptions of Feedback Delays**

Published in *Climatic Change*

### **Human Control of Climate Change**

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## 2.1 Abstract

The use of analogies and repeated feedback might help people learn about the dynamics of climate change. In this paper, we study the influence of repeated feedback on the control of a carbon-dioxide (CO<sub>2</sub>) concentration to a goal level in a Dynamic Climate Change Simulator (DCCS) using the “bathtub” analogy. DCCS is a simplification of the complex climate system into its essential elements: CO<sub>2</sub> concentration (stock); man-made CO<sub>2</sub> emission (inflow); and natural CO<sub>2</sub> removal or absorption in the atmosphere (outflow). In a laboratory experiment involving DCCS, we manipulated feedback delays in two ways: the frequency of emission decisions and the rate of CO<sub>2</sub> absorption from the atmosphere (climate dynamics). Our results revealed that participants' ability to control the CO<sub>2</sub> concentration generally remained poor even in conditions where they were allowed to revise their emission decisions frequently (i.e., every two years) and where the climate dynamics were rapid (i.e., 1.6% of CO<sub>2</sub> concentration was removed every year). Participants' control of the concentration only improved with repeated feedback in conditions of lesser feedback delay. Moreover, the delay due to climate dynamics had a greater effect on their control than the delay due to emission decisions frequency. We provide future research directions and highlight the potential of using simulations like DCCS to help people learn about dynamics of Earth's climate.

*Keywords:* Dynamic decision making; simulation; climate change; stocks and flows; bathtub metaphor, feedback delay

## 2.2 Introduction

Growing evidence indicates that people do not understand accumulation processes even in simple dynamic systems that include a single stock (or accumulation), a single inflow rate that increases the stock, and a single outflow rate that decreases the stock (Booth Sweeney and Sterman 2000; Cronin and Gonzalez 2007; Cronin et al. 2009; Sterman and Booth Sweeney 2002). In fact, even people with strong background in mathematics and sciences fail to interpret a basic principle of dynamic systems: a stock rises (or falls) when the inflow exceeds (or is less than) the outflow (Cronin et al. 2009).

Climate is a complex dynamic system that presents important challenges for its perception, interpretation, and understanding by the general public (Bostrom et al. 1994; Moxnes and Saysel 2009; Read et al. 1994; Sterman and Booth Sweeney 2007). It has been shown that people rely upon a simple but erroneous heuristic called the correlation heuristic, whereby they wrongly believe that system outputs are positively correlated with inputs. For the climate system, relying on the correlation heuristic means incorrectly assuming that stabilizing emissions (inputs) would rapidly stabilize GHG concentration (output); and emissions cuts would quickly reverse GHG concentration (Sterman and Booth Sweeney 2002, 2007). Consequently, people who rely on this heuristic are likely to defer acting on climate change (wait-and-see behavior) because they significantly underestimate the delay between reductions in GHG emissions and reductions in GHG concentration (misperceptions of feedback), and the magnitude of emissions reductions needed to stabilize the concentration.

According to the misperceptions of feedback (MOF) hypothesis (Sterman 1989), people ignore the actions in a dynamic system that involves feedback delays. In the case

of the climate system, the MOF hypothesis suggests that people likely fail to account for the long time delays between increases in carbon-dioxide (CO<sub>2</sub>) emissions and the subsequent increases in CO<sub>2</sub> concentration, and those between increases in CO<sub>2</sub> concentration and its effects on increasing atmospheric temperature. An increase in emissions does not increase concentration and atmospheric temperature immediately, but after a long delay where it might be too late to act to avoid significant impact.

Moxnes and Sagsel (2009) have built on Sterman and Booth Sweeney's (2007) study by focusing on how people regulate CO<sub>2</sub> emissions to reach an attainable concentration goal in a simulated climate system. They tested participants' ability to control the concentration to 300 GtC above the pre-industrial level in a period between the years 2000 and 2100, where participants decided on emissions every 10 years. They tested participants in different conditions that mimicked the working of the climate system, with repeated feedback about decisions and the resulting changes in CO<sub>2</sub> concentration. Participants entered ten numbers which represented their emission decisions every ten years over a 100 year period. In all but one feedback condition, participants entered *all* ten emissions at one time and then saw the effects of their decisions. In the conditions without feedback, Moxnes and Sagsel's (2009) results coincided with the static, onetime, paper-and-pencil climate policy task's results from Sterman and Sweeney (2007): Participants showed a general tendency to overshoot the goal level and to rely on the correlation heuristic in their emission decisions. In the feedback condition, however, Moxnes and Sagsel (2009) gave participants the ability to make repeated emission decisions every 10 years and to observe the effects of these decisions. Within a 10 year period, the emissions remained constant at values which were

set at the start of the period. Results show that providing repeated feedback helped participants change their strategy over time, and may have helped them to reduce their reliance on the correlation heuristic and misperceptions of feedback.

In this paper, we build on prior studies by utilizing an interactive and dynamic stock-management simulation (Gonzalez and Dutt 2011). This task, called the Dynamic Climate Change Simulation (DCCS),<sup>5</sup> is used to investigate people's ability to control CO<sub>2</sub> concentration to a goal level under different kinds of feedback delays for inputs (CO<sub>2</sub> emissions) and outputs (CO<sub>2</sub> removal or CO<sub>2</sub> absorptions). Our main objective is to investigate the reasons for poor control over dynamic systems, particularly in the context of climate change, and to discover possibilities in which these problems can be overcome.

The DCCS utilizes the graphical "bathtub metaphor" proposed by Sterman and Booth Sweeney (2007) and expands upon the feedback manipulation presented by Moxnes and Saysel (2009). The bathtub metaphor is a common analogy used to explain the behavior of dynamic systems (Sterman 2000), and it has also been used to communicate the complex dynamics of the climate system (Kunzig 2009). DCCS is different from the simulation used in Moxnes and Saysel (2009) because it is an *interactive* simulation where participants make emission decisions repeatedly after a certain number of time periods. The emission, absorption, and concentration information is represented graphically on the DCCS's interface. According to Moxnes and Saysel's (2009) results, one would expect less reliance on the correlation heuristic and MOF, and less wait-and-see behavior given the transparency in DCCS. Furthermore, by

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<sup>5</sup> The DCCS simulation can be downloaded for free under an academic license from: [http://downloads.ddmlab.com/?action=form&package\\_id=2](http://downloads.ddmlab.com/?action=form&package_id=2)

manipulating the frequency of feedback, we expect participants to improve their strategy in controlling CO<sub>2</sub> concentration more often and over several time periods of interaction with the task (Moxnes and Saysel 2009). However, there are currently several open questions regarding how helpful feedback frequency and the historical information provided in a simulation is to learning control (Moxnes and Saysel 2009).

In general, research is needed to develop interventions to help people learn about the dynamics of climate. Simulation tools like DCCS may help overcome the reliance on MOF and correlation heuristic by giving direct experience with the accumulation processes and feedback delays involved. Research is also needed to compare people's understanding using tools like DCCS in contrast to other forms of information presentation, including descriptive information such as the Intergovernmental Panel on Climate Change (IPCC) reports (Houghton et al. 2001), one-shot climate policy task (Sterman and Booth Sweeney 2007), or simulations with no feedback (Moxnes and Saysel 2009). In this regard, an initial evaluation of DCCS was performed to investigate the effects of repeated feedback on subsequent performance in Sterman and Sweeney's (2007) climate policy task (Dutt and Gonzalez 2010). In that study, we provided participants with experiences of future CO<sub>2</sub> concentration in DCCS. One group was first asked to control the concentration in DCCS to a predefined goal trajectory over 100 time periods. This group was later given Sterman and Sweeney's (2007) climate policy task, which asked them to sketch the emission and absorption corresponding to a CO<sub>2</sub> concentration trajectory over 100 time periods. A separate group of participants did not experience DCCS and were immediately given the climate policy task. Results showed that participants with experiences in DCCS were able to reduce their reliance on

correlation heuristic and MOF in their sketches compared to participants without DCCS experiences. Thus, the repeated feedback in DCCS enabled participants to answer subsequent climate policy task more accurately.

In this paper, we study the effects of two delay types in repeated feedback that are present in emission and absorption on participants' ability to control the concentration in DCCS. One type of feedback delay is the frequency of emission decisions. Moxnes and Saisel (2009) kept this delay fixed at 10 emission decisions in increments of 10 years each, while we vary the frequency at two levels: high, every 2 years; and low, every 4 years. The second type of feedback delay manipulated is the climate dynamics: variations in the rate of natural CO<sub>2</sub> absorption in DCCS. Moxnes and Saisel (2009) also discussed how current uncertainty in our understanding of absorption processes might influence our ability to control the concentration. In this paper, we test this idea by manipulating the climate dynamics in DCCS at two levels: slow, 1.2% of CO<sub>2</sub> concentration per year; and rapid, 1.6% of CO<sub>2</sub> concentration per year).

These two feedback delays in CO<sub>2</sub> emission (inflow) and CO<sub>2</sub> absorption (outflow) are of two very different kinds. Frequency delay of emission decisions is similar to production delay (Diehl and Sterman 1995), but it is feed-forward for climate (i.e., people need to anticipate future emissions that affect CO<sub>2</sub> concentration). Thus, what is set as emissions policies now is held constant in DCCS for a certain number of time periods (years) in the future. On the other hand, feedback delay in the climate dynamics determines the speed with which CO<sub>2</sub> is absorbed from the atmosphere in each time period. This feedback delay is outside of the participants' direct control, and it is an inherent part of the climate system simulated in DCCS.

In this paper, it is hypothesized that:

**H1:** In DCCS, slower climate dynamics and less frequent emission decisions would result in poorer human control of the CO<sub>2</sub> concentration to a goal level, compared to faster dynamics and more frequent decisions.

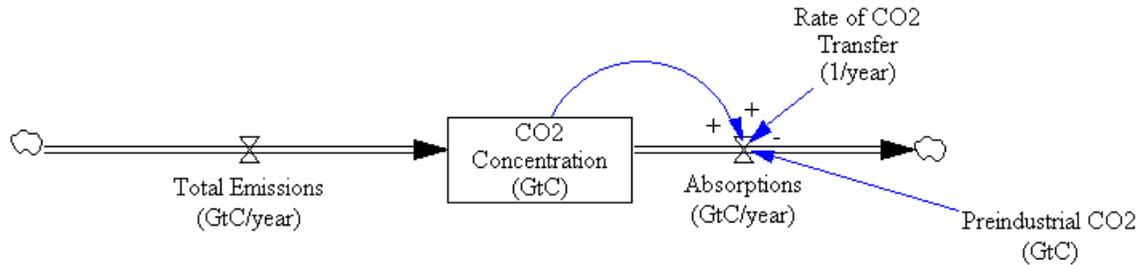
This hypothesis is supported by prior evidence of how the MOF hypothesis and feedback delays generally hinder human control in dynamic tasks (Brehmer 1989; Diehl and Sterman 1995; Dörner 1980; Paich and Sterman 1993; Sterman 1989). In addition, both the climate dynamics and frequency of emission decisions have been identified as particularly hard to understand by the general public (Cramer et al. 2001; Joos et al. 2001; Matear and Hirst 1999; Moxnes 2004; Moxnes and Sarsel 2009; Sarmiento and Quéré 1996; Sterman and Booth Sweeney 2007), though it is hard to determine beforehand which of these two delays would be more problematic in DCCS.

In what follows, we first motivate the development of DCCS and its capabilities. Then, details of an experiment where the two feedback delays were manipulated are provided. Finally, we provide experimental results, and discuss their implications for improving understanding and future research.

### **2.3 A Simplified Model of the Earth's Climate**

Figure 2-1 provides the system-dynamics representation of a simple climate model used in DCCS (for Vensim® PLE model equations refer to the supplementary material). The *CO<sub>2</sub> Concentration* represents the accumulation in the atmosphere which increases indirectly from an inflow of man-made CO<sub>2</sub> emissions called *Total Emissions* (made of two kinds of emissions: fossil-fuel and deforestation). The outflow of *Absorptions* causes a decrease in *CO<sub>2</sub> Concentration* due to CO<sub>2</sub> absorbed by terrestrial

and oceanic ecosystems. As long as *Total Emissions* exceed *Absorptions*, *CO<sub>2</sub> Concentration* continues to increase. Only when *Total Emissions* equal *Absorptions* will *CO<sub>2</sub> Concentration* stabilize at a particular level. The arrow from *CO<sub>2</sub> Concentration* into *Absorptions* illustrates that the *Absorptions* are a function of *CO<sub>2</sub> Concentration* at all times and are assumed to be directly proportional to *CO<sub>2</sub> Concentration*.



**Figure 2-1. The simple climate model. The *CO<sub>2</sub> Concentration* represents the stock or accumulation in the atmosphere. The *CO<sub>2</sub> concentration* increases indirectly by man-made (or anthropogenic) *Total Emissions* (i.e., inflow). The *Rate of CO<sub>2</sub> Transfer* is a constant multiplier into *CO<sub>2</sub> Concentration* that gives rise to *Absorptions* after the *Preindustrial CO<sub>2</sub>* (the 1970 baseline *CO<sub>2</sub> concentration*) has been subtracted from the *CO<sub>2</sub> Concentration*.**

This model representation is very similar to the example of filling and draining a bathtub (the *bathtub metaphor*) (Sterman 2000). The *Rate of CO<sub>2</sub> Transfer* in the model is a constant multiplier in *CO<sub>2</sub> Concentration* that gives rise to *Absorptions* after the *Preindustrial CO<sub>2</sub>* (the 1970 baseline *CO<sub>2</sub> concentration*) has been subtracted from *CO<sub>2</sub> Concentration* (the *Preindustrial CO<sub>2</sub> concentration* is assumed to be due to natural *CO<sub>2</sub> emissions*). The use of a baseline concentration and year enables us to determine the change in *Absorptions* values.

The model can be represented mathematically as:

$$d(\text{CO}_2 \text{ Concentration})/dt = \text{CO}_2 \text{ Emissions} - \text{Absorptions} \quad (1)$$

Where *Absorptions* are defined as:

$$\text{Absorptions} = \text{Rate of CO}_2 \text{ transfer} * (\text{CO}_2 \text{ Concentration} - \text{Preindustrial CO}_2)^6(2)$$

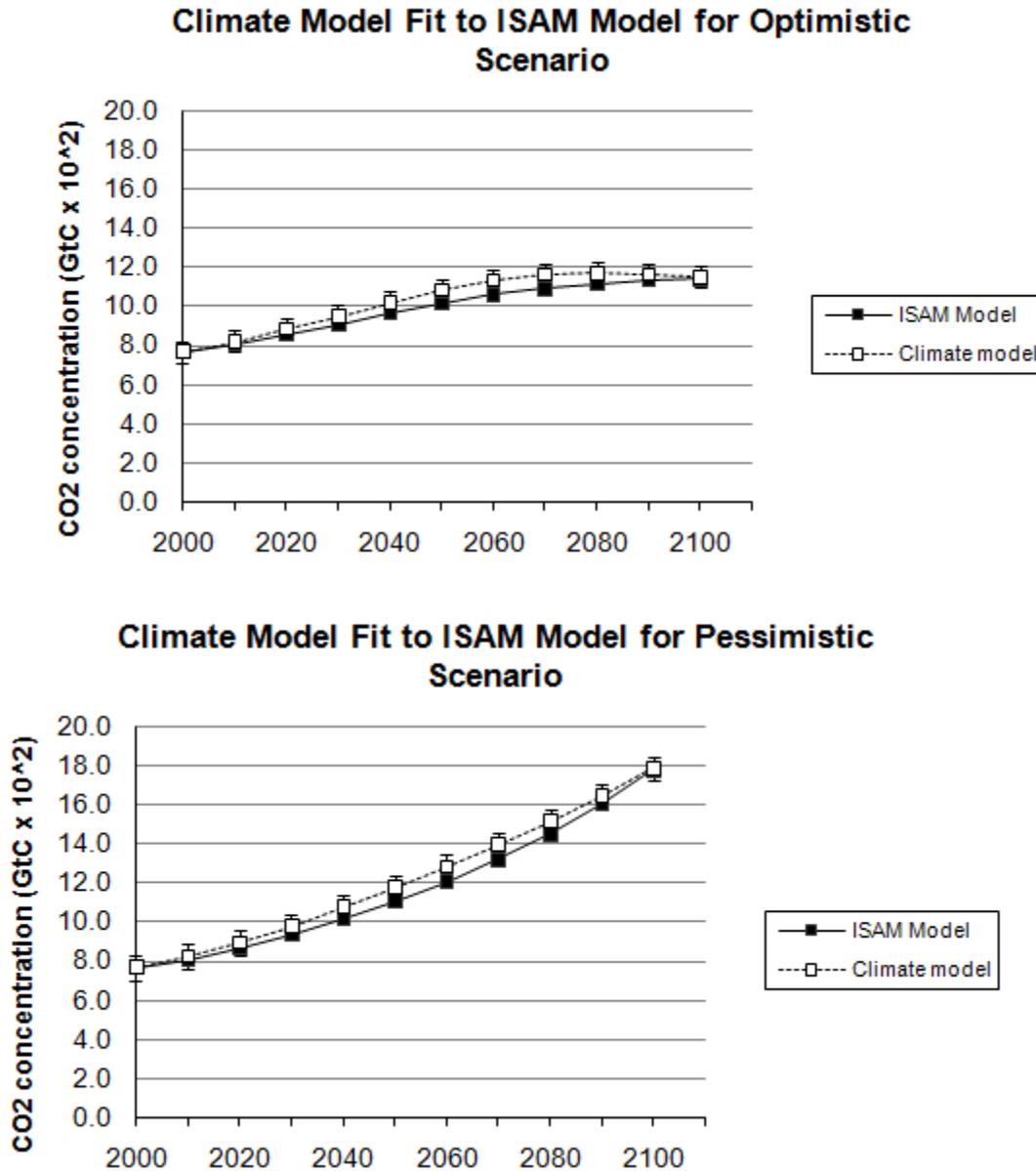
This simple climate model was calibrated between years 2000 and 2100 with projections given by two different and extreme emission scenarios from the 2001 IPCC report (Houghton et al. 2001; Nakicenovic et al. 2000). A popular carbon-dioxide dynamics model, called the Integrated Science Assessment Model (ISAM), was used to predict *CO<sub>2</sub> Concentration* for the two emission scenarios: an "optimistic" and a "pessimistic" scenario (Jain et al. 1994). The scenarios are storylines about potential courses of future emissions. For details on the ISAM model, scenarios, and our calibration exercise, please refer to the supplementary material.

After calibrating our simple climate model with the ISAM model, we found that the *Rate of CO<sub>2</sub> Transfer* was 0.016 of the *CO<sub>2</sub> concentration* per year in the optimistic scenario and 0.012 of the *CO<sub>2</sub> concentration* per year in the pessimistic scenario. The calibration of our model's predictions for *CO<sub>2</sub> concentration* with the ISAM model's predictions is shown in Figure 2-2. The top and bottom panels show the calibration in the optimistic and pessimistic scenarios, respectively. For the optimistic scenario,  $R^2 = .97$ ,  $\text{RMSD} = .50 \text{ GtC}$  for a *Rate of CO<sub>2</sub> Transfer* = 1.6% of *CO<sub>2</sub> concentration*. For the pessimistic scenario,  $R^2 = .99$ ,  $\text{RMSD} = .50 \text{ GtC}$  for a *Rate of CO<sub>2</sub> Transfer* = 1.2% of *CO<sub>2</sub> concentration*. Therefore, our model closely replicates results from a more

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<sup>6</sup> The units of *CO<sub>2</sub> Concentration* are GtC (Giga or  $10^9$  tons of carbon) and represent the *CO<sub>2</sub> concentration* in the atmosphere above its preindustrial level. The units of *Total Emissions* and *Absorptions* are GtC per year (Giga tons of carbon per year). The *Rate of CO<sub>2</sub> Transfer* is the amount of *CO<sub>2</sub>* absorbed in a single year with units of percentage (%) per year. The inverse of the *Rate of CO<sub>2</sub> Transfer* yields the average residence time of *CO<sub>2</sub>* in the atmosphere. As a cautious reader would have observed, the *Rate of CO<sub>2</sub> Transfer* is assumed to be a constant for the model.

mechanistic ISAM model and represents realistic predictions of future  $CO_2$  concentration based upon those two *Rates of  $CO_2$  Transfer*.



**Figure 2-2. Top panel: The simple climate model calibrated to ISAM model's predictions in the optimistic scenario,  $R^2=.97$ , RMSD = .50, Rate of  $CO_2$  Transfer = 0.016. Bottom panel: The simple climate model calibrated to ISAM model's predictions in the pessimistic scenario,  $R^2=.99$ , RMSD = .50, Rate of  $CO_2$  Transfer = 0.012. In both figures, error bars show 90% confidence interval around the average estimate.**

Those two *Rates of CO<sub>2</sub> Transfer* were used to manipulate the feedback delay due to climate dynamics. Later, we used this model as the scientific basis to design DCCS.

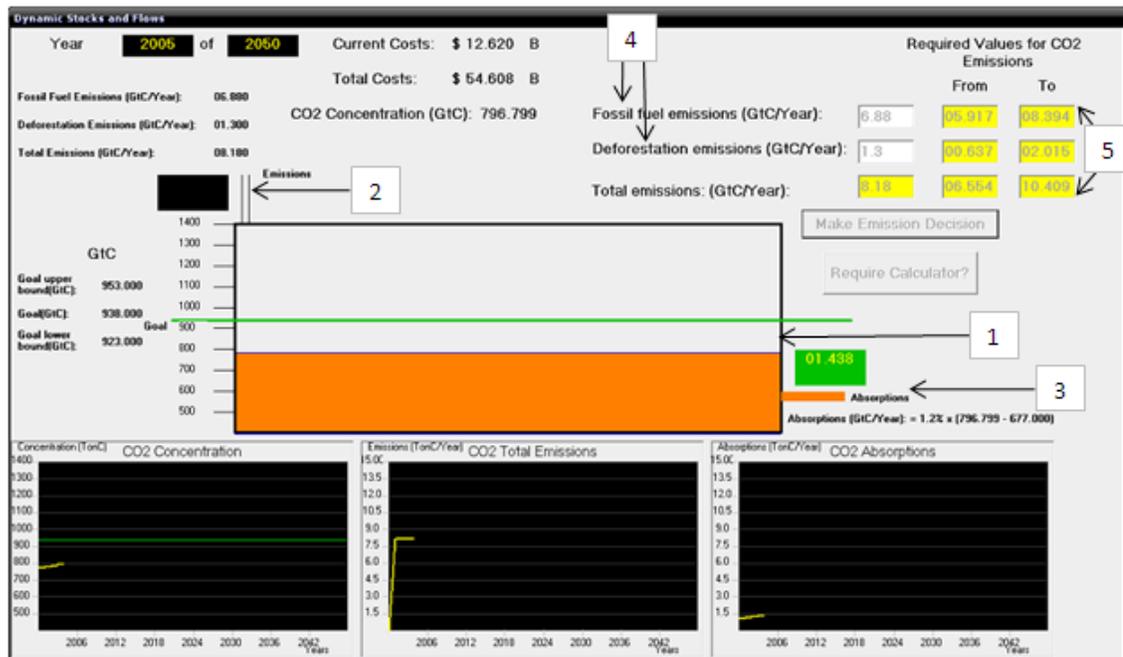
## 2.4 Dynamic Climate Change Simulator (DCCS)

DCCS was built on the simple climate model described above, and was inspired by a generic dynamic stock and flows task (Gonzalez and Dutt 2011) and ideas from an earlier study by Moxnes and Sagsel (2009). The interface, shown in Figure 2-3, presents a single stock, CO<sub>2</sub> concentration, as an orange-colored liquid in a tank which metaphorically represents Earth's atmosphere (Figure 2-3-1). The participants' aim is to maintain the CO<sub>2</sub> concentration within an acceptable range around an attainable goal level of 938 GtC (= 450 ppmv). The level is shown with a green horizontal line labeled *Goal*. Participants are asked to keep the concentration within +/- 15 GtC of the goal level (*Goal upper bound (GtC)* and *Goal lower bound (GtC)* define the upper and lower bounds of this range). The current time period's *CO<sub>2</sub> Concentration* is presented on the y-axis, and it is also displayed as a label above the tank.

In the 1992 *Dynamic Integrated Climate Economy model* (or DICE-92; Nordhaus 1992) and in the real world, there are two major man-made sources of CO<sub>2</sub> emissions: from deforestation and land use, and from burning fossil-fuels, especially in transportation, power generation, and industry. In DCCS, participants decide on both emission types (Figure 2-3-4). These two emissions are summed, and their addition represents the *Total Emissions* represented on the interface by a pipe connecting the top-left of the tank (Figure 2-3-2). Based upon the IPCC report (Houghton et al. 2001), the starting proportions of fossil-fuel emissions in *Total Emissions* is 80% and starting deforestation emissions constitute only 20%. Below the *Year* range, information on the

last time period's *Fossil Fuel Emissions (GtC/Year)*, *Deforestation Emissions (GtC/Year)*, and *Total Emissions (GtC/Year)* is displayed.

*Absorptions*, represented by a pipe on the bottom right of the tank (Figure 2-3-3), are proportional to CO<sub>2</sub> concentration and decrease the concentration according to our simple climate model. The absorption equation and its values are also shown on the interface (see Figure 2-3).



**Figure 2-3. Dynamic Climate Change Simulator (DCCS) task (see description in text).**

Participants set emissions in the boxes respectively labeled *Fossil fuel emissions (GtC/year)* and *Deforestation emissions (GtC/year)*, and then clicked the *Make Emission Decision* button. This causes DCCS to implement these emissions as *Total Emissions* and to provide feedback on the CO<sub>2</sub> concentration resulting from *Total Emissions* and *Absorptions*.

To avoid extreme exploration in participants' emission decisions, the fossil-fuel and deforestation emissions were restricted to the values between the *From* and *To* ranges (Figure 2-3-5). These ranges provide realistic bounds on the possible increases and decreases in emissions, and reflect realistic emission policies in the real world. The *From* value ensures that emissions reductions do not underestimate world economic growth and energy requirements. At the same time, the *To* value allows for economic growth and a more fossil-fuel intensive economy. The *From* value does not allow participants to cut their yearly emissions immediately, while the *To* value allows participants to increase their yearly emissions by only certain amounts. The values in these ranges are dynamic and are calculated after each emission decision is executed. The *From* and *To* range for fossil-fuel emissions was set at -14% to +22% of the value of its current emissions. For deforestation emissions, the *From* and *To* range was set at -51% to +55% of its current emissions. The exact values were derived after analyzing the maximum and minimum values of current and future emissions across different emission scenarios (Jain et al. 1994). To see how these ranges were determined, please refer to the supplementary material of the paper.

There are three graphical displays provided at the bottom of DCCS's interface. The display on the left shows the current and past CO<sub>2</sub> concentrations across several time periods up to the current time point in the simulation (the simulation year is shown in the top-left corner of the interface). Displays in the middle and on the right show the current and past total CO<sub>2</sub> emissions and CO<sub>2</sub> absorptions, respectively.

In DCCS, each time a participant is unable to keep the concentration within the goal range, she incurs a cost penalty based upon the IPCC report (Houghton et al. 2001).

The penalty (in \$) represents damages due to climate change in the time participants take to control the CO<sub>2</sub> concentration to the goal. It is assumed to be \$100 million per GtC times the difference between the goal and the current CO<sub>2</sub> concentration (in GtC). Participants do not incur this penalty if they maintain the concentration within the permissible range around the goal. Current and accumulated penalties are shown as the *Current Costs* and *Total Costs*.

After participants enter their emissions values and click *Make Emission Decision*, DCCS automatically moves forward by a number of simulated years. During each of the transit years until DCCS stops again, *Total Emissions* are maintained at the same constant values initially entered. This procedure is similar to establishing an emission policy that is kept constant for a number of planned years. After that number of years, participants can again decide on new values for emissions based upon the current and past CO<sub>2</sub> concentrations. This repeated decision-feedback process carries on until the final year is reached.

## 2.5 Experiment

When emission decisions are made less frequently, there is a larger gap between two consecutive decisions. Due to the MOF hypothesis and feedback delay in emission decisions, poorer performance in DCCS is expected when decisions are less frequent compared to when they are more frequent.

Different climate dynamics were induced by taking two *Rates of CO<sub>2</sub> Transfer* values, which result in different CO<sub>2</sub> absorptions in DCCS (Eq. 2). We used a 1.6% per year rate (optimistic scenario, rapid dynamics) and a 1.2% per year rate (pessimistic scenario, slow dynamics). When climate dynamics are slow, the feedback delay in DCCS

increases and poorer performance is expected compared to a situation where the climate dynamics are rapid.

Although any kind of feedback delay is expected to produce sub-optimal control over the CO<sub>2</sub> concentration, this experiment helps us determine which of these two feedback delays produces a more detrimental effect and how they interact to determine how people learn about climate dynamics under different dynamic conditions. These feedback delays are important representations of the actual delays in man-made emission decisions and in the real world climate system where the latter is beyond the direct human control. For example, climate meetings and negotiations (i.e., the frequency of emission decisions) have become nearly annual events since 1996.<sup>7</sup> Also, it is expected that oceans (Matear and Hirst 1999; Sarmiento and Quéré 1996) and plants would reduce their ability to absorb CO<sub>2</sub> due to the increases in CO<sub>2</sub> concentration (Cramer et al. 2001; Joos et al. 2001). Therefore, it is important to consider the variations in climate dynamics and its effects on human learning.

As mentioned, the climate dynamics combined with the frequency of emission decisions is expected to hamper human learning and result in increased difficulties in the control of CO<sub>2</sub> concentration in DCCS. Specifically, a situation with slower climate dynamics (i.e., 1.2% rate of CO<sub>2</sub> transfer) combined with less frequent emission decisions (i.e., every 4 years) is expected to result in the poorest performance. Due to these long feedback delays involved, participants who are unable to foresee the long-term effects of their decisions are likely to show overshooting and undershooting in their attempts to reach the goal level. It is also likely that only a smaller proportion of participants are able

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<sup>7</sup> See a list of previous Congress of Parties (COP) meetings at: <http://unfccc.int/meetings/archive/items/2749.php>

to reach and stabilize the CO<sub>2</sub> concentration within the goal range, and that they would need more time periods to do so. This oscillatory (sinusoidal) behavior in CO<sub>2</sub> concentration trajectory over time is similar to that observed in other complex dynamic control systems (Forrester 1961; Sterman 1989). In contrast, higher frequency of emission decisions (i.e., every 2 years) combined with rapid climate dynamics (i.e., 1.6% rate of CO<sub>2</sub> transfer) is expected to result in the best control of the concentration in DCCS.

## **2.6 Methods**

### **2.6.1 Experimental Design**

Participants were randomly assigned to one of four between-subjects conditions: *rapid-high*, where the rate of CO<sub>2</sub> transfer is 1.6% per year with emission decisions made every 2 simulated years; *rapid-low*, where the rate of CO<sub>2</sub> transfer is 1.6% per year with emission decisions made every 4 simulated years; *slow-high*, where the rate of CO<sub>2</sub> transfer is 1.2% per year with emission decisions made every 2 years; and *slow-low*, where the rate of transfer is 1.2% per year with CO<sub>2</sub> emission decisions made every 4 years.

Participants' target under all four conditions was to maintain the CO<sub>2</sub> concentration within a +/- 15 GtC range around a 938 GtC (~450 ppmv) goal value. In order to equalize the number of decisions made in all four conditions to 50 decisions each, the rapid dynamics condition ran for 100 simulated years and the slow dynamics condition for 200 years. The DCCS started in the year 2000 where the initial CO<sub>2</sub> concentration was fixed at 769 GtC, the real-world value of CO<sub>2</sub> concentration that year

(Houghton et al. 2001). Similarly, the initial deforestation emissions were fixed at 1.3 GtC/year and the initial fossil-fuel emissions at 6.88 GtC/year (Houghton et al. 2001).

The value of the CO<sub>2</sub> concentration goal (= 938 GtC) was deliberately set above 2000's CO<sub>2</sub> concentration (= 769 GtC ~ 370 ppmv). That is because attainable goals in the real-world are set higher than the status-quo concentration with an expectation that emission reductions will be immediately initiated to attain these goals. In addition, the goal used in our experiment corresponds to the IPCC's "best-case" stabilization scenario (Houghton et al. 2001, pg. 76). Goal values that are higher than 2000's actual concentration were also used by Moxnes and Sagsel (2009). Setting the goal higher than the status-quo concentration is also necessary to make the goal realistically achievable and to account for the practical inability to drastically reduce emissions. A participant may try to increase emissions initially. Again, this increase mimics the pattern of real-world emissions, which are accelerating (see CSIRO Australia, December 8, 2006 for more details). The main implication of achieving the goal in our experiment is to attain control over the CO<sub>2</sub> concentration to levels that are considered safe for Earth's climate. Thus, participants who manage to do so do not incur any costly penalties. The more time participants take to reach and maintain the concentration within the goal range, the more it will cost them.

Across all conditions, the CO<sub>2</sub> concentration will stabilize at the goal when total emissions equal CO<sub>2</sub> absorptions. This means that when climate dynamics are slow, the optimal value of total emissions should equal  $(938 - 677) * 0.012 = 3.13$  GtC per year. Similarly, when climate dynamics are rapid, the optimal value of total emissions should equal  $(938 - 677) * 0.016 = 4.18$  GtC per year (Eq. 2).

The optimal combination of emission values was calculated to reach the goal in the minimum number of time periods for each condition. These values are irrespective of the frequency of emission decisions. Therefore, if a participant is able to decrease total emissions from the initial value of 8.18 GtC per year to the corresponding optimal values, then that participant would be able to optimally hit the goal and stabilize the concentration at the goal.

We use the absolute value of the discrepancy as the main dependent variable (absolute discrepancy measures the deviation from a goal and equals the absolute value of the difference between the goal and CO<sub>2</sub> concentration). Also, we used fossil-fuel, deforestation, and total emissions as other dependent variables to investigate participants' decision-making strategies in a regression model.

## **2.6.2 Participants**

Fifty-three graduate and undergraduate students from diverse fields of study participated in this experiment, 26 were females. Ages ranged from 18 years to 54 years (Mean= 26 years, SD= 8 years). In self-reports, 64% of participants indicated having heard of climate change through television, websites, or movies; 25% reported having read something about climate change through newspapers or magazines; and the remaining 11% reported having knowledge on the subject through some other means. Also, 70% of participants reported they either completed or are currently pursuing degrees in science, technology, engineering, and management (STEM).

Fourteen participants were randomly assigned to the slow-low condition and thirteen participants were assigned to each of the slow-high, rapid-high, and rapid-low conditions, respectively. All participants received a base pay of \$5 for a 30-minute study.

Participants could also earn an additional bonus of no more than \$3, which was based on their performance in DCCS. If a participant deviated outside the goal range in any given time period, then a cost penalty was incurred that was calculated as the product of \$100 million and the absolute discrepancy in that time period. Participants incurring more than \$400 billion in accumulated costs were paid a bonus of \$0. Participants incurring less than or equal to \$15 billion in accumulated costs were paid a bonus of \$3. All other accumulated costs between \$15 billion and \$400 billion were linearly transformed to actual dollar payments. Four hundred billion dollars is four times the accumulated cost incurred if one entered the optimal values for total emissions for the slow climate dynamics. Therefore, the upper limit on the penalty was not very stringent and still enabled them to explore and learn from their decisions and repeated feedback. Similarly, a \$15 billion lower bound was kept to ensure that the initial discrepancy between the concentration and the goal range's lower bound in the starting year did not penalize participants.

### **2.6.3 Procedure**

Participants were given instructions before starting the DCCS task. The instructional text given in the slow-low condition is provided in the supplementary material. After participants read the instructions, they were shown a video of what would happen in DCCS if the status-quo total emissions (=8.18 GtC) were maintained for the next 50 years. Climate dynamics in this video were set at their manipulated value of 1.2% or 1.6% of the CO<sub>2</sub> concentration per year depending upon the condition. The main intention was to motivate participants and to make them understand what would happen if they maintained the status quo emissions for the next 50 years. Starting in the year

2000, the video's CO<sub>2</sub> concentration crossed the 938 GtC goal value and increased to more than 1000 GtC by the year 2050, which is more than a 5% increase from 2000's value. After watching the video, participants were asked to imagine the severe consequences this increase would have on the world's climate. Participants only watched the video and did not interact with DCCS at this point. In addition, 2000's fossil-fuel and deforestation emissions values were used throughout the demonstration and the same video was shown to all participants in all conditions. Showing the video could possibly anchor and bias participants' judgments. But this bias does not constitute a problem in the experiment because believing that CO<sub>2</sub> emissions need to change or fall does not necessarily help people understand when and by how much these emissions need to be reduced.

After the video, participants were reminded of the requirements in DCCS. They were then asked to play DCCS for 50 decision points over a course of 100 or 200 years depending upon the condition.

## **2.7 Results**

### **2.7.1 General Performance: Discrepancy from Goal**

Figure 2-4 shows the average absolute discrepancy in each condition (the absolute discrepancy is averaged over all participants and decision points in a condition).

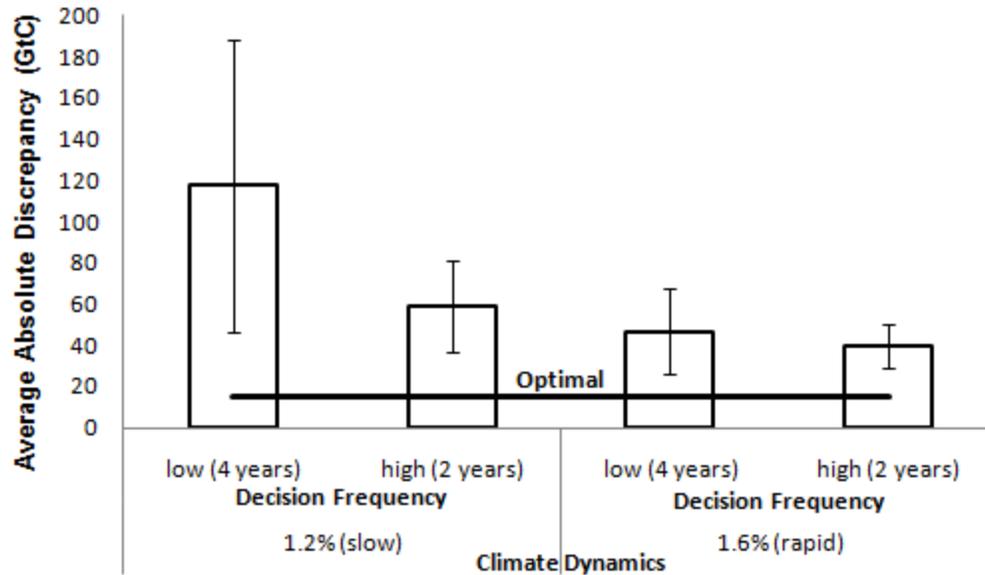
Participants were clearly not performing optimally. The average absolute discrepancy is greater than the optimal goal range (the black line showing "Optimal" is the upper bound at 15 GtC of the goal range) in all conditions. The distribution of discrepancies in all four conditions was non-normal. Normality of the dependent variable in our data was tested

for on the 1st, 25th, and 50th decision points in all four conditions.<sup>8</sup> Levene's test for homogeneity of variances for the dependent variable revealed that the variance in the data were non-homogenous at those points,  $F(3, 49) = 2.668, p < .05$ ;  $F(3, 49) = 7.561, p < .05$  and  $F(3, 49) = 10.136, p < .05$ , respectively.

A nonparametric Kruskal-Wallis test reported that the effect of different conditions on the absolute value of the discrepancy was significant ( $H(3) = 12.120, p < .05$ ). In fact, the average absolute discrepancy was greater when the emission decisions frequency was low (*Median* = 61.77 GtC) compared to when it was high (*Median* = 45.57 GtC),  $U = 267.00, Z = -3.00, p < .01, r = -.21$ . In addition, the average absolute discrepancy was greater when climate dynamics were slow (*Median* = 61.67 GtC) compared to when they were rapid (*Median* = 37.42 GtC),  $U = 182.00, Z = -3.00, p < .01, r = -.41$ . Thus, the hypothesis is supported: participants' control of the CO<sub>2</sub> concentration is poorer when the climate dynamics were slow and the emission decisions were made less frequently compared to when the climate dynamics were rapid and the emission decisions were made more frequently.

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<sup>8</sup> We tested for normality of the dependent variable on the 1<sup>st</sup>, 25<sup>th</sup>, and 50<sup>th</sup> decision points in all four conditions. For the 1<sup>st</sup> decision point, the data was normal in the rapid-high and slow-high conditions,  $D(13) = .913, ns$  and  $D(13) = .930, ns$ , respectively; however, it was non-normal for the slow-low and rapid-low conditions,  $D(14) = .776, p < .05$  and  $D(13) = .862, p < .05$ , respectively. For the 25<sup>th</sup> decision point, the data was normal for the rapid-high and slow-high conditions,  $D(13) = .887, ns$  and  $D(13) = .924, ns$ , respectively; however, it was non-normal for the slow-low and rapid-low conditions,  $D(14) = .606, p < .05$  and  $D(13) = .819, p < .05$ , respectively. Lastly, for the 50<sup>th</sup> decision point, the data was non-normal in all conditions, i.e., rapid-high ( $D(13) = .655, p < .05$ ), slow-high ( $D(13) = .650, p < .05$ ), slow-low ( $D(14) = .819, p < .05$ ), and rapid-low ( $D(13) = .627, p < .05$ ), respectively.



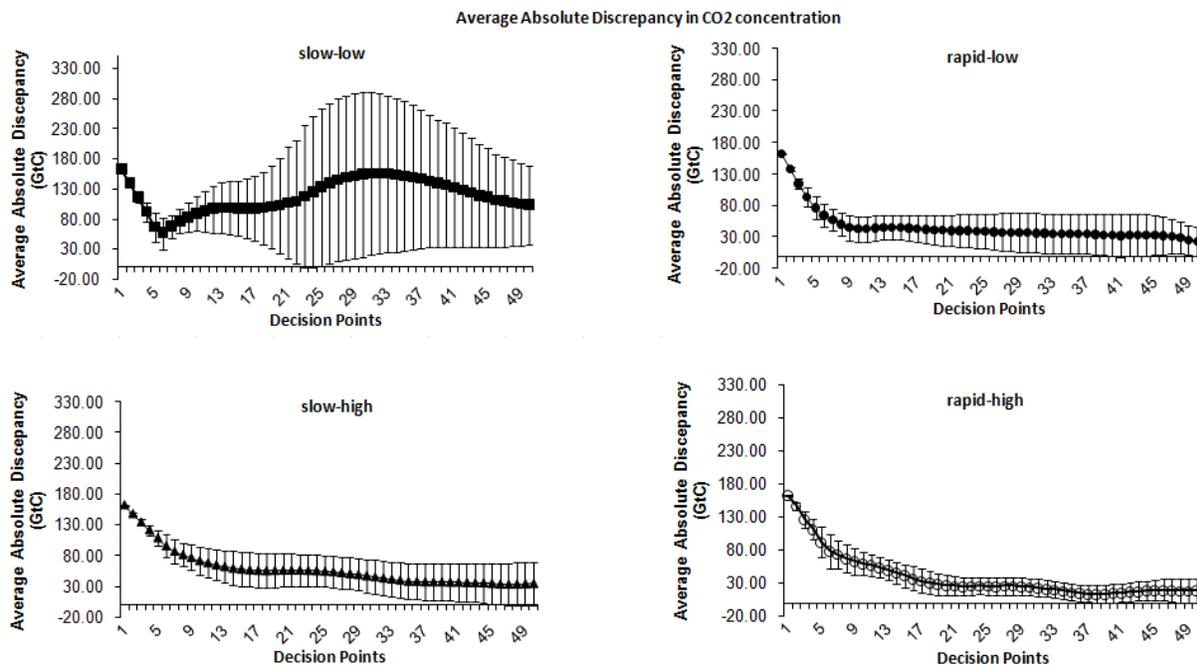
**Figure 2-4. Average Absolute Discrepancy (GtC) in the four conditions (this discrepancy is averaged over all participants and decisions points in a condition). Participants have more difficulty achieving control of CO<sub>2</sub> concentration when climate dynamics are slow than rapid and when the frequency of emission decisions is low than high. Error bars show 90% confidence interval around the average estimate. The line labeled “Optimal” shows the optimal value around the goal of 15 GtC (if participants kept their Average Absolute Discrepancy within the goal range then they should be below the optimal). Absolute Discrepancy was more than the “Optimal” value in all conditions. Readers wanting to convert the result to ppmv can use a 0.47 ppmv to 1 GtC conversion ratio.**

Post-hoc pair-wise comparisons for the average absolute discrepancy revealed the following: slow–low condition (*Median* = 79.40 GtC) > rapid-high condition (*Median* = 40.34 GtC),  $U = 26.00$ ,  $Z = -3.154$ ,  $p < .01$ ,  $r = -.43$ ; slow–high (*Median* = 52.78 GtC) was no different from rapid-low (*Median* = 32.74 GtC),  $U = 64.00$ ,  $Z = -1.051$ ,  $ns$ ,  $r = -.14$ ; rapid–high (*Median* = 40.34 GtC) was no different from rapid-low (*Median* = 32.74 GtC),  $U = 83.00$ ,  $Z = -0.077$ ,  $ns$ ,  $r = -.01$ ; slow–low (*Median* = 79.40 GtC) > slow-high (*Median* = 52.78 GtC),  $U = 53.00$ ,  $Z = -3.000$ ,  $p < .01$ ,  $r = -.25$ ; slow–low (*Median* = 79.40 GtC) > rapid-low (*Median* = 32.74 GtC),  $U = 37.00$ ,  $Z = -2.620$ ,  $p < .01$ ,  $r = -.36$ ;

and rapid-high (*Median* = 40.34 GtC) was no different from slow-high (*Median* = 52.78 GtC),  $U = 55.00$ ,  $Z = -1.513$ ,  $ns$ ,  $r = -.21$ .

## 2.7.2 Learning Effects

Figure 2-5 shows the average absolute discrepancy in each of the four conditions over 50 decision points (each point within each condition is averaged over all participants in that condition). As expected, the discrepancy in the slow-low condition shows a sinusoid oscillation above the optimal value across all 50 decision points. In addition, according to the confidence intervals, the slow-low condition has the greatest variability in human behavior.



**Figure 2-5. Average Absolute Discrepancy in CO<sub>2</sub> concentration in the slow-rapid and low-high conditions over 50 decision points (this discrepancy is averaged over all participants in a condition for every decision point). Error bars show 90% confidence interval around the average estimate. Readers wanting to convert the result to ppmv can use a 0.47 ppmv to 1 GtC conversion ratio.**

In each of the four conditions, the average absolute discrepancy changed significantly over 50 decision points according to a nonparametric Friedman's ANOVA test ( $\chi^2(49) = 371.02, p < .001$ ;  $\chi^2(49) = 230.51, p < .001$ ;  $\chi^2(49) = 296.17, p < .001$ ; and  $\chi^2(49) = 97.40, p < .001$  for the rapid-high, rapid-low, slow-high, and slow-low conditions, respectively). There was no difference in the average absolute discrepancy between the 1st decision point (*Median* = 163.27 GtC) and the 50th decision point (*Median* = 59.32 GtC) in the slow-low condition,  $T = 23, p > .05, r = -.35$ . In contrast, this difference was significant in the other three conditions. The average absolute discrepancy in the rapid-high, slow-high, and rapid-low conditions was significantly greater for the 1st decision point (*Median* = 161.57 GtC; *Median* = 163.04 GtC; and *Median* = 162.80 GtC respectively) compared to the 50th decision point (*Median* = 5.66 GtC; *Median* = 8.24 GtC; and *Median* = 11.97 GtC), with,  $T = 0, p < .001, r = -.62$ ;  $T = 1, p < .001, r = -.61$  and  $T = 0, p < .001, r = -.62$ , respectively. These results suggest that the repeated feedback in DCCS enabled participants to learn about the dynamics of the simulated climate system in all conditions but slow-low. In the slow-low condition, learning is offset by the presence of strong oscillations in discrepancy due to excessive feedback delays. These results also demonstrate DCCS' effectiveness in helping participants learn how to stabilize their CO<sub>2</sub> concentration in three out of the four conditions; however, these three conditions are those that have comparatively less feedback delay than the slow-low condition.

## 2.7.3 Participants' Strategies

### 2.7.3.1 Reaching and stabilizing within the goal range

The time it took participants' CO<sub>2</sub> concentration to reach the goal range for the first time and their ability to keep it within the goal range thereafter were analyzed. The proportion of participants that reached the goal range for the first time was smaller when climate dynamics were slow (*Mean* = 78%) compared to when they were rapid (*Mean* = 96%),  $U = 286.50$ ,  $Z = -1.97$ ,  $p < .05$ ,  $r = -.27$ . The frequency of emission decisions had no effect on the proportion of participants reaching the goal. Furthermore, we classified participants as "stabilizing at the goal," if their CO<sub>2</sub> concentration was maintained within the goal range for eight consecutive time periods after it initially came within the goal range. The proportion of participants stabilizing at the goal was significantly smaller when climate dynamics were slow (*Mean* = 41%) compared to when they were rapid (*Mean* = 65%),  $U = 286.00$ ,  $Z = -1.97$ ,  $p < .05$ ,  $r = -.27$ . Again, frequency of emission decisions had no effect on the proportion of participants stabilizing at the goal. These results suggest that human control behavior is significantly driven by the climate dynamics and less so by the frequency of emission decisions.

### 2.7.3.2 Ratio of fossil-fuel to total emissions

To understand participants' choices between the two emission types, the ratio of fossil-fuel emissions to total emissions was analyzed. Fossil-fuel emissions constituted on average 96% of total emissions and deforestation emissions only the remaining 4%. However, these percentages did not change significantly as a function of different conditions. These results indicate that participants chose fossil-fuel emissions as the

primary means of controlling their CO<sub>2</sub> concentration over the deforestation emissions overall.

### 2.7.3.3 Distance of emissions from *To* value

A reason for greater discrepancy in conditions of greater feedback delay might be that participants maintain the fossil-fuel and deforestation emissions closer to the *To* value in the range of emissions. When emissions are closer to the *To* side of the range, it also indicates participants' attempt to increase emissions faster. An analysis of fossil-fuel and deforestation emissions' distances to the *To* value revealed that fossil-fuel emissions were on average only 36% away from the *To* value and the deforestation emissions were on average only 42% away. Therefore, participants generally kept emissions closer to the *To* values. Furthermore, this strategy for the two types varied with condition (fossil-fuel emissions:  $H(3) = 12.044, p < .01$ ; deforestation emissions:  $H(3) = 7.800, p < .05$ ). Fossil-fuel and deforestation emissions were significantly closer to the *To* value when climate dynamics were slow (*Median* = 28%; *Median* = 25%) compared to when they were rapid (*Median* = 45%; *Median* = 38%),  $U = 168.00, Z = -3.26, p < .001, r = -.45$  and  $U = 206.00, Z = -2.58, p < .01, r = -.35$ , respectively. Again, the frequency of emission decisions did not influence the distance to the *To* value.

Detailed comparisons show that both emissions were significantly closer to the *To* value in the slow–low condition (*Median* = 25%, *Median* = 26%) compared to the rapid–high condition (*Median* = 38%, *Median* = 48%),  $U = 32.00, Z = -2.692, p < .01, r = -.52$  and  $U = 33.00, Z = -2.641, p < .01, r = -.52$ , respectively. Thus, these results show that participants kept emissions closer to the *To* value of the *From* – *To* range in conditions of longer feedback delay.

## 2.7.4 Decision Rule: Emission Decisions

Similar to other stock-management problems (Sterman 1989), the decision rule used to determine CO<sub>2</sub> emissions can be adapted to the DCCS task: emissions are a function of CO<sub>2</sub> concentration and CO<sub>2</sub> absorptions. We developed three regression models to predict each of the following: the average Total Emissions (TE), the average Fossil-fuel Emissions (FE), and the average Deforestation Emissions (DE).

Predictor variables were calculated as the average of the 50 decision points for each participant. This gave a dataset of 53 data points (one point for each participant) for the purpose of three multiple regression models with the following predictors:

*A*: CO<sub>2</sub> absorptions

*D*: Discrepancy (Goal – Amount)

*FE<sub>from</sub>*: Fossil-fuel emissions' *From* Value

*FE<sub>to</sub>*: Fossil-fuel emissions' *To* Value

*DE<sub>from</sub>*: Deforestation emissions' *From* Value

*DE<sub>to</sub>*: Deforestation emissions' *To* Value

*Ratio<sub>FossilToTotal</sub>*: Ratio of fossil-fuel emissions to Total emissions

*DistanceFossil<sub>from</sub>*: Distance of fossil-fuel emissions from the *From* value

*DistanceDeforestation<sub>from</sub>*: Distance of deforestation emissions from the *From* value

In addition, we kept two dummy {0, 1} variables to test for the effects of different conditions:

*FR*: Frequency of emission decisions (*FR*=1 for low, i.e., every 4 years; *FR*=0 for high, i.e., every 2 years)

*CD*: Climate Dynamics (*CD*=1 for slow, i.e., 1.2% of CO<sub>2</sub> concentration; *CD*=0 for rapid, i.e., 1.6% of CO<sub>2</sub> concentration)

*e*: Residual

The following equations were used in each of the three models:

Model 1

$$\begin{aligned}
 FE = & b_0 + b_1 D + b_2 A + b_3 FE_{\text{from}} + b_4 FE_{\text{to}} + b_5 \text{Ratio}_{\text{FossilToTotal}} + b_6 \\
 & \text{DistanceFossil}_{\text{from}} \\
 & + b_7 CD + b_8 FR + e \quad (3)
 \end{aligned}$$

Model 2

$$\begin{aligned}
 DE = & b_0 + b_1 D + b_2 A + b_3 DE_{\text{from}} + b_4 DE_{\text{to}} + b_5 \text{Ratio}_{\text{FossilToTotal}} \\
 & + b_6 \text{DistanceDeforestation}_{\text{from}} + b_7 CD + b_8 FR + e \quad (4)
 \end{aligned}$$

Model 3

$$\begin{aligned}
 TE = & b_0 + b_1 D + b_2 A + b_3 FE_{\text{from}} + b_4 FE_{\text{to}} + b_5 DE_{\text{from}} + b_6 DE_{\text{to}} + b_7 \\
 & \text{Ratio}_{\text{FossilToTotal}} \\
 & + b_8 \text{DistanceFossil}_{\text{from}} + b_9 \text{DistanceDeforestation}_{\text{from}} + b_{10} CD + b_{11} FR + e \\
 & (5)
 \end{aligned}$$

When *CD* = 0 and *FR* = 0, the three resulting models generate predictions for the rapid-high condition, which is the condition with the least feedback delay and best participants' performance. Therefore, values of the standardized beta coefficients (*b<sub>x</sub>*) in these models are relative to the rapid-high condition.

Table 2-1 provides the results of ordinary least-squares linear regression involving these models. As seen in Table 2-1, model 1 (*p* < .001) accounted for 92.7% of the

variance in fossil-fuel emissions. The only standardized beta coefficients that were significant were the *From* and *To* ranges for fossil-fuel emissions. Both of these standardized beta coefficients also possessed strong positive values, i.e., an increase in the *From* or *To* predictors caused an increase in fossil-fuel emissions while holding all other predictors constant. Participants did take the values of the *From* and *To* ranges into account while making their fossil-fuel emissions, and moreover the ranges caused participants to increase fossil-fuel emissions.

**Table 2-1. Regression output of the three models.**

	<b>Model 1</b>			<b>Model 2</b>			<b>Model 3</b>		
	<b>Fossil Emissions<sup>a</sup></b>			<b>Deforestation Emissions<sup>a</sup></b>			<b>Total Emissions<sup>a</sup></b>		
<b>R<sup>2</sup></b>	0.927			0.929			1.00		
<b>Adjusted R<sup>2</sup></b>	0.916			0.918			1.00		
<b>F (N=53 participants)</b>	81.612***			83.724***			15192.61***		
<b>Variables</b>	<b>B</b>	<b>SE B</b>	<b>β</b>	<b>B</b>	<b>SE B</b>	<b>β</b>	<b>B</b>	<b>SE B</b>	<b>β</b>
<b>Constant</b>	2.384	2.384		0.795	0.819		0.155	0.300	
<b>Discrepancy</b>	-0.002	-0.007	-.134	-0.002	0.001	-.536	-0.001	0.000	-.060*
<b>Absorptions</b>	-0.273	0.555	-.217	-0.165	0.115	-.593	0.126	0.043	-.093**
<b>From Fossil Emissions</b>	1.191	0.217	.999***				1.176	0.020	.929***
<b>To Fossil Emissions</b>	0.839	0.153	.999***				0.829	0.014	.929***
<b>From Land Emissions</b>				1.974	0.219	.959***	2.267	0.093	.226***
<b>To Land Emissions</b>				0.624	0.069	.959***	0.717	0.030	.226***
<b>Ratio Fossil To Total</b>	-1.181	1.499	-.042	-0.251	0.628	-.040	0.415	0.216	.014*
<b>Distance Fossil From</b>	0.725	1.090	.039				0.330	0.093	.017***
<b>Distance Deforestation From</b>				0.161	0.087	.096*	0.024	0.030	.003
<b>CD</b>	0.145	0.497	.060	0.016	0.111	.302	0.131	0.038	.050***
<b>FR</b>	0.143	0.170	.060	0.006	0.024	.012	0.019	0.017	.007

Note: <sup>a</sup> Dependent Variable for model 1: *FE*, for model 2: *DE* and for model 3: *TE*. \*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ . N =53 participants (i.e., we averaged 50 decision points for each participant). B refers to non-standard beta coefficients. SE B is the standard error in B. β refers to standard beta coefficient (which can be used for magnitude comparison in the models)

Model 2 ( $p < .001$ ) accounted for 92.9% of the variance in the deforestation emissions. Similar to Model 1, the standardized beta coefficients of the *From* and *To* ranges for deforestation emissions were significant and positive. The standardized beta coefficient of the distance of deforestation emissions from the *From* value was also significant and positive. These findings are consistent with the reasoning that participants who maintained their deforestation emissions father away from the *From* value, or kept them closer to the *To* value, were bound to cause significant increases in their deforestation emissions.

Model 3 ( $p < .001$ ) accounts for 100% of the variance in total emissions. Firstly, the standardized beta coefficients of Discrepancy and CO<sub>2</sub> absorptions predictors were negative and significantly affected total emissions. As per our simple climate model, CO<sub>2</sub> absorptions are proportional to the concentration and thus also proportional to the discrepancy. In addition, participants in DCCS need to decrease emissions from a higher value to make it equal to absorptions in order to control CO<sub>2</sub> concentration (the absorptions were less than total emissions initially in the year 2000). Due to the same reason, the correlation between total emissions and CO<sub>2</sub> absorptions should be negative if participants were able to control the concentration within the goal range. The decrease in total emissions on account of an increase in Discrepancy and absorptions predictors indicates that participants decreased their total emissions from the greater initial 2000 value in different conditions. Participants do learn to control the CO<sub>2</sub> concentration over repeated time periods as they decrease their total emissions when their Discrepancy predictor increases.

In addition, consistent with the previous two regression models, the standardized beta coefficients of the *From* and *To* ranges in model 3 for both emission types significantly affected the total emissions. The effect of the *From* and *To* ranges for fossil-fuel emissions on the total

emissions (beta coefficient = .929) exceeded that of the *From* and *To* ranges for deforestation emissions (beta coefficient = .226) when all other predictors were maintained at their constant values.

Furthermore, the standardized beta coefficients for the *RatioFossilToTotal* and *DistanceFossilFrom* predictors were positive and significantly affected total emissions. The effect of these two predictors on total emissions validates earlier findings that participants predominantly used fossil-fuel emissions to control the CO<sub>2</sub> concentration. Finally, climate dynamics (determined by *CD* dummy) significantly affected the total emissions. This observation is also consistent with the earlier finding where the discrepancy and therefore CO<sub>2</sub> concentration resulting from total emissions was greater with slower climate dynamics (as shown in Figure 2-4). The frequency of emission decisions did not influence total emissions. Furthermore, the magnitude of standardized beta coefficient for emission decisions frequency (*FR* dummy) was less than the standardized beta coefficient for climate dynamics (*CD* dummy variable). The significance and magnitude of the standardized beta coefficients for the *CD* and *FR* dummy variables show that climate dynamics played a significantly greater role compared to decision frequency when comparing their individual effects on total emissions.

## **2.8 Discussions and Conclusions**

Many of the complex dynamic effects found in the real world can be better understood with simple tasks (Cronin et al. 2009), and a demonstration of such a process for a simulated climate system was presented here in DCCS. The complex problem was simplified into its essential elements: CO<sub>2</sub> concentration, and CO<sub>2</sub> emissions and absorptions over time. DCCS was built from a simple climate model, and it was used to investigate participants' ability to control the system under different conditions of feedback delays: frequency of emission decisions and

climate dynamics. Results show that a change in climate dynamics from rapid to slow (when averaged across the frequency of emission decisions) deteriorated participants' control of CO<sub>2</sub> concentration compared to a change in frequency of emission decisions from high to low (when averaged across the climate dynamics). This supports many previous results on people's inability to understand basic dynamics and to control an accumulation in the presence of feedback delays (Brehmer 1989; Diehl and Sterman 1995; Dörner 1980; Gonzalez 2005; Sterman 1989). Despite the poor performance, participants improved their control over the CO<sub>2</sub> concentration over many time periods in DCCS for three out of the four conditions. These three conditions are those where the feedback delay was the least.

Emission decisions frequency results are consistent with previous findings in a simulated climate system (Moxnes and Sagsel 2009) and in other dynamic systems (Diehl and Sterman 1995; Paich and Sterman 1993). Participants' control performance deteriorates as a function of increasing delays in the inflow and outflow. The effects created by delays in our study are similar to the cause-and-effect relationships that determine the fate of the population in Dörner and Kimber's (1997) study, where participants had to increase the well-being of fictitious occupants in the presence of long feedback delays between their decision actions and outcomes.

Furthermore, we find evidence of the MOF hypothesis in our results on account of the oscillatory behavior found in CO<sub>2</sub> concentration for the slow-low condition. In this study, participants started below the goal and were asked to stabilize the concentration within the goal range as quickly as possible. These requirements caused participants to rapidly increase emissions in the initial period of performance to bring their concentrations closer to the goal as quickly as possible. However, participants soon realized that their CO<sub>2</sub> emissions were too high

to stabilize the concentration and thus their concentration trajectories tended to overshoot the goal range.

We argue that participants' poor control is likely due to their failure to reduce CO<sub>2</sub> emissions in DCCS. To be successful in this task, participants need to *slowly* reduce emissions, but instead we found their emissions to be closer to the *To* value of emissions range. The late realization that emissions are too high when participants reach the goal range produces an attempt to reduce emissions when it is already too late (the coefficients of absorptions and discrepancy in regression model 3 were negative, showing that overall participants do try to reduce total emissions on account of these two predictors). This late correction causes a "bullwhip" sinusoidal oscillation, which is well known in dynamic systems with feedback delays (Sterman 1989) and a sign of the MOF. One possible explanation for the greater effect of climate dynamics is the saliency and nature of the feedback delay in emission decisions. Fossil-fuel and deforestation emissions are directly controlled and manipulated by participants in all conditions from one decision point to the next. Repeatedly making emission decisions and observing their effects might force participants to notice the delay present in their direct controls. Furthermore, repeatedly making decisions enables participants to anticipate the future effects of emissions. This explanation is supported by the fact that prior research has found similar effects for repeated feedback and how it improves performance in a control task similar to DCCS (Dutt and Gonzalez 2008a, 2008b).

Participants' control only improved in those conditions that offered comparatively less feedback delays. In future research, we plan to investigate learning over many repeated performances in DCCS. Prior work in dynamic decision making literature suggests that participants' initial performance in interactive management flight simulators is generally quite

poor, but they can improve due to repeated performances (Brehmer 1989; Diehl and Sterman 1995; Dörner and Kimber 1997; Sterman, 1989). This finding of learning-by-doing is intuitive, and it is one of the strengths of management flight simulators that we could test DCCS for in the future. In the current experiment, participants faced the same conditions in a single performance and thus, may have improved solely as a function of repetition, without developing any generic understanding about accumulation or how to handle time delays. Following the work of Diehl and Sterman (1995) and Paich and Sterman (1993), we would like to vary the learning parameters in DCCS from one performance to the next without revealing these variations to participants. This manipulation is likely a better test of participants' understanding of the principles of accumulation. For example, we would like to vary key parameters such as the climate dynamics and then assess participants' knowledge of the relevant processes (i.e., the stock-flow structure, controlling atmospheric CO<sub>2</sub> concentrations, the impact of feedback from CO<sub>2</sub> concentrations, etc.) using a pre-test and post-test design. As part of the pre- and post-test, participants' knowledge may be tested outside the context of the simulator by using Sterman and Booth Sweeney's (2007) climate policy task.

Management flight simulators are becoming increasingly common and may be used by the IPCC to supplement its forthcoming assessment reports.<sup>9</sup> In the real world, people are more likely to be exposed to traditional descriptive text and figures that describe the projected impacts of different climate policies. Here, people must make judgments about when and by how much emissions must decline to meet any goal for either the CO<sub>2</sub> concentration or temperature change (such as stabilizing at CO<sub>2</sub> at 450 ppmv or with warming  $\leq 2$  °C). Because prior research shows that people cannot make such judgments reliably, one would like to know if the chance to

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<sup>9</sup> For example: <http://climateinteractive.org>; <http://scripts.mit.edu/~jsterman/climate/master/>; <http://www.astr.ucl.ac.be/users/matthews/jcm/>; and <http://www.google.com/landing/cop15/>

explore these dynamics through a simulator might help them improve their understanding of these issues in common settings. These settings might include reading media reports or other information about future climate change, and the policy options to control it. As mentioned above, Dutt and Gonzalez (2010) have found DCCS to be effective in helping people to understand the dynamics of CO<sub>2</sub> concentration. A group of participants, who experienced DCCS, improved their performance in the succeeding Sterman and Booth Sweeney's (2007) climate policy task compared to another group of participants who performed the climate policy task directly. As part of future research, we would also like to know what features of simulations are most helpful in building people's understanding of climatic processes – as the examples above illustrate, existing simulators vary widely in their level of detail in regards to the carbon cycle, other greenhouse gases, radiative forcing, and other climate processes in their interface designs, use of graphics and video, and in many other attributes. Therefore, it might be interesting to evaluate what features enable the most effective learning. A future study centered on investigating a simulator's greatest features would make a vitally needed contribution to our understanding of the critical processes in risk communication for climate change and other issues involving complex dynamic systems.

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## **2.11 Next Chapter's Highlights**

The next chapter discusses people's reliance on correlational or linear thinking as a cognitive factor for their wait-and-see behavior. Furthermore, this chapter discusses how performance in DCCS influences people's wait-and-see behavior among those with and without STEM backgrounds.

## **Chapter 3: Correlational Thinking and Repeated Feedback**

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### **Decisions from experience reduces misconceptions about climate change**

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### 3.1 Abstract

Research has shown widespread misconceptions in public understanding of the dynamics of climate change: a majority of people incorrectly infer that carbon-dioxide (CO<sub>2</sub>) concentrations can be controlled by stabilizing emissions at or above current rates (correlation heuristic), and while emissions continuously exceed absorption (violation of mass balance). Such misconceptions delay actions that can mitigate climate change. This paper tests a way to reduce these misconceptions through experience in a dynamic simulation. In a laboratory experiment, participants were randomly assigned to one of two conditions: *description*, where participants performed a CO<sub>2</sub> stabilization (CS) task that provided them with a CO<sub>2</sub> concentration trajectory over a 100 year period and asked them to sketch the corresponding CO<sub>2</sub> emissions and absorption over the same period; and *experience*, where participants performed the same task in a dynamic climate change simulator (DCCS), followed by the CS task. In both conditions, half of the participants were science and technology (STEM) majors, and the other half were non-STEM. Results revealed a significant reduction in people's misconceptions in the *experience* condition compared to the *description* condition. Furthermore, STEMs demonstrated better performance than non-STEMs. Policy implications highlight the potential for using experience-based simulation tools like DCCS to improve understanding about the dynamics of climate change.

*Keywords:* Decisions from description; Decisions from experience; misconceptions; repeated feedback; STEM; non-STEM.

## 3.2 Introduction

Despite strong scientific consensus about the causes and risks of climate change, the general public exhibits a complacent attitude towards actions that benefit Earth's climate (Bostrom, Morgan, Fischhoff, & Read, 1994; Leiserowitz, 2007; Read, Bostrom, Morgan, Fischhoff, & Smuts, 1994; Weber, 2006). Recent surveys have shown that most Americans exhibit *wait-and-see* behavior; they infer that reductions in greenhouse gas (GHG) emissions can be deferred until there is greater evidence that climate change is harmful (Leiserowitz, 2007; Sterman & Booth Sweeney, 2002, 2007). For example, 60% of participants in a survey in the U.S. chose either “until we are sure that global warming is really a problem, we should not take any steps that would have economic costs,” or “its effects will be gradual, so we can deal with the problem gradually” (Kull, 2001). This wait-and-see behavior is also seen among people outside the U.S., with a large majority favoring to “wait-and-see” or “go-slow” in Russia, China, and India (Leiserowitz, 2007), and also among policymakers: “slow the growth of greenhouse gas emissions (GHGs), and – as the science justifies – stop, and then reverse that growth” (G. W. Bush, 2/14/02; Jones, 2002). According to Jones (2002), G. W. Bush believed that climate mitigation actions could be taken at a slow pace until science confirmed climate change as a real problem.

Furthermore, some scientists also seem to possess a stronger wait-and-see (inaction) view on climate change. For example, Fred Singer, professor emeritus of environmental sciences at the University of Virginia and an ex-member of the U.S. National Advisory Committee on Oceans and Atmosphere, recently commented: “Human activities are not influencing the global climate in a perceptible way. Climate will continue to change, as it always has in the past, warming and cooling on different time scales and for different reasons, regardless of any human

action” (Singer, 2009, p. 1). Thus, Singer argues that human activity has no influence on climate change whatsoever, which would result in inaction rather than a slow wait-and-see action. Moreover, climate initiatives like the Kyoto Protocol and Clear Skies, that have pledged to mitigate the global warming problem, have also expressed support for wait-and-see behavior: the Kyoto Protocol’s proposed reductions in emissions fall short of the proposed targets and Clear Skies’ initiative promotes even further greenhouse gas emissions growth (Sterman & Booth Sweeney, 2002, 2007).

Wait-and-see behavior would work well in simple systems that have short delays between the detection of a problem and the implementation of corrective actions. For example, one can afford to wait-and-see when boiling beans until steam builds up and the cooker whistles because there is a short delay between the whistle and removing the cooker from the flame. Unfortunately for a complex system like Earth’s climate, there are much longer delays between the decision to mitigate emissions and the corresponding changes in atmospheric GHG concentrations (IPCC, 2007; Sterman, 2008; Sterman & Booth Sweeney, 2002, 2007). Prior research shows that people often ignore long feedback delays in complex systems (Sterman, 1989), and people who exhibit wait-and-see behavior might be acting under the implicit misconception of very short delays in Earth’s climate system (Sterman, 2008; Sterman & Booth Sweeney, 2002, 2007). As there are long feedback delays, however, people’s wait-and-see behavior would become problematic. Because even if mitigation actions are taken, atmospheric CO<sub>2</sub> accumulation would continue to rise until emissions fell below the absorption rate. Average atmospheric temperature would then peak, and consequences such as rising sea levels and thermal expansion would continue (Wigley, 2005; Meehl, Washington, Collins et al., 2005). Therefore, wait-and-see behavior is likely to

cause abrupt, persistent, and costly regime changes on Earth in the future (Alley, Marotzke, Nordhaus et al., 2003; Scheffer et al., 2001).

Prior research has shown that people's misconceptions about the climate system are related to their own deficient mental models:<sup>10</sup> the general public lacks training in climatology and has little understanding of climate processes (Bostrom et al., 1994; Kasemir, Dahinden, Swartling et al., 2000; Kempton, 1997; Morgan, Fischhoff, Bostrom, & Atman, 2002; Palmgren, Morgan, de Bruin, & Keith, 2004; Read et al., 1994). In this paper, however, we argue that people's misconceptions about the climate system are due to a more fundamental limitation of their mental models: a weak understanding of accumulation and mass balance. Cronin, Gonzalez, and Sterman (2009) have demonstrated that as the relationship between inflows and outflows become more complex, people tend to rely more on simple but erroneous heuristics. According to Cronin et al. (2009), people rely on the "correlation heuristic," whereby they wrongly infer that the system's accumulations are positively correlated to its inflows.

Sterman (2008) and Sterman and Booth Sweeny (2007) have shown that people's wait-and-see behavior on climate is related to their reliance on the correlation heuristic. For climate, relying on the correlation heuristic means that people wrongly infer that an accumulation (CO<sub>2</sub> concentration) follows the same path as the inflow (CO<sub>2</sub> emissions); hence, stabilizing emissions would rapidly stabilize the concentration, and emissions cuts would quickly reduce the concentration and damages from climate change. Consequently, people who rely on the heuristic would demonstrate wait-and-see behavior because they would significantly underestimate the delay between reductions in CO<sub>2</sub> emissions and in the CO<sub>2</sub> concentration. They would also

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<sup>10</sup> By "mental model" we mean a person's inferences or judgments about the networks of causes and effects that describe how a system operates which include the system's boundary (i.e., factors are considered endogenous or exogenous) and its time horizon. Therefore, in this paper, the term "mental model" refers to participants' inferences about shapes of CO<sub>2</sub> emissions and absorption overtime.

underestimate the magnitude of emission reductions needed to stabilize the concentration. Furthermore, Sterman and Booth Sweeny (2007) have also shown that people's wait-and-see behavior is also related to the violation of mass balance, whereby people incorrectly infer that atmospheric CO<sub>2</sub> concentration can be stabilized even when emissions exceeds absorption. Violating mass balance leads to wait-and-see behavior because people think the current state of the climate system, where emissions are double absorption (IPCC, 2007), would not pose a problem to future stabilization.

Research has evaluated wait-and-see behavior in terms of correlation heuristic reliance and mass balance violation in a one-shot paper-and-pencil climate stabilization (CS) task (Sterman, 2008; Sterman & Booth Sweeney, 2007). In the CS task, participants are asked to sketch CO<sub>2</sub> emissions and absorptions that would stabilize the CO<sub>2</sub> concentration to an attainable goal by the year 2100. In this problem, people are given the concentration's starting value in the year 2000, and its historic trends and emissions between the years 1850 and 2000. Sterman and Booth Sweeney (2007) report that about 70% of participants (about 60% of whom had backgrounds in science, technology, engineering, and management (STEM), and a majority of the rest in economics) sketched CO<sub>2</sub> emissions that were positively correlated with CO<sub>2</sub> concentration. Moreover, 74% of participants violated mass balance in their responses either by failing to keep emissions greater than absorption before the concentration stabilized in the year 2100; or failing to make emissions equal to absorption when the concentration reached 2100.

Sterman (2008) and Sterman and Booth Sweeney (2007) made a qualitative claim that using simulation-based tools can likely help people correct their misconceptions about Earth's climate. Other researchers also suggest that experiencing the adverse consequences of climate change is likely to improve people's understandings of the climate system (Weber, 2006).

However, the efficiency of simulation tools in reducing people's reliance on the correlation heuristic and the violation of mass balance has only been demonstrated in some initial attempts (Dutt & Gonzalez, 2009, 2011; Moxnes & Saisel, 2009). Moxnes and Saisel (2009) used a simulated computer task where participants were required to stabilize the CO<sub>2</sub> concentration by making emissions decisions every 10 simulated years starting in the year 2010. After every 10 years elapsed, participants could see the changes in the concentration as a result of their decisions. Moxnes and Saisel (2009) demonstrated that better emission decisions are possible through providing repeated feedback about decision actions and outcomes to participants. Feedback empowers participants to try new hypotheses and also to understand the cause-and-effect relationships between their decisions and outcomes.

Building on these results, we developed a very simplified but interactive computer-based simulation of the climate system called the Dynamic Climate Change Simulator (DCCS), and used it to collect data on how participants control the atmospheric CO<sub>2</sub> accumulation to a goal under different conditions of feedback delays (Dutt & Gonzalez, 2009, 2011). The two types of manipulated feedback delays employed in the DCCS were the natural delays in CO<sub>2</sub> absorption, and the frequency with which multiannual emission policies are revised for a simulated climate system. We found that participants improved their control of the CO<sub>2</sub> concentration through experiences gained in DCCS, where these experiences might have enabled participants to revise their existing mental models. But again, the efficiency of simulation tools has not been fully demonstrated.

### **3.3 Current Research**

Given people's widespread misconceptions about the climate system, research is critically needed to show how their misperceptions (relying on the correlation heuristic and

violating mass balance) can be overcome through experience in simulation tools. The main objective of this paper is to evaluate whether or not experiencing repeated outcome of decisions (i.e., feedback) in DCCS reduces participant's misconceptions about our climate.

DCCS provides repeated feedback on the changes in the CO<sub>2</sub> concentration each year as a result of CO<sub>2</sub> emissions and absorption policies set by participants, allowing participants to observe results of their decisions as they try to control the concentration to a goal. We compare participants' responses to the CS task after previously making repeated decisions in DCCS to other participants' responses in the CS task where they were not given the DCCS experience. We expect that repeated feedback in DCCS will affect the responses made in the CS task. The null hypothesis is:

**H1:** There is no difference in the misconceptions (relying on the correlation heuristic and violating mass balance) for participants who receive repeated feedback and those who do not receive repeated feedback.

Research has observed misconceptions in the CS task among participants both with and without a scientific (STEM) background (Serman & Booth Sweeney, 2007). Serman and Booth Sweeney (2007) have suggested that the technical background of STEM participants does not reduce their reliance on the correlation heuristic or their violation of mass balance. But they have not tested STEMs' and non-STEMs' misconceptions (relying on correlation heuristic and violating mass balance) systematically; they have not tested the background or the relationship of background to their performance in the CS task. Considering the widespread misconceptions prevalent among scientists, general public, and policymakers (Nordhaus, 1994), it becomes important to determine the value of a STEM education in reducing misconceptions. In this regard, psychological research has found that novices in a problem often focus on the surface

(i.e., irrelevant) features of a problem, rather than on more fundamental underlying structural features (Chi, Feltovich, & Glaser, 1981; Gonzalez & Wong, in press). According to Schoenfeld (1982), this difference in focus on the surface versus the structure is affected by a person's background in mathematics and sciences. A person with a STEM background possesses far greater experience in mathematical and scientific problem-solving compared to someone with a non-STEM background. The mathematical background is expected to help STEMs focus more on the structure of the task compared to non-STEMs, and enable STEMs nurture fewer misconceptions about the climate system compared to non-STEMs. The null hypothesis is:

**H2:** There is no difference in misconceptions (relying on correlation heuristic and violating mass balance) of people from STEM backgrounds and people from non-STEM backgrounds.

### **3.4 Methods**

To test our hypotheses, we conducted a laboratory experiment using STEM and non-STEM participants who either performed the CS task only (*description* condition), or completed DCCS then followed by the CS task (*experience* condition).

#### **3.4.1 Participants**

One hundred and twenty participants from Carnegie Mellon University and from the surrounding Pittsburgh area were invited to participate through an online advertisement and were randomly assigned to either the *description* or *experience* condition (60 participants in each condition). Out of the 60 participants in each condition, 30 were from STEM backgrounds and 30 were from non-STEM backgrounds. STEM backgrounds included majors in the fields of science, technology, engineering, management, economics, and medicine. Non-STEM backgrounds included majors in the fields of the arts, social sciences, and the humanities. Among

the 120 participants, 2 were pursuing Ph.D. degrees, 48 were pursuing Masters or MBA degrees, and 70 were pursuing undergraduate degrees. Fifty-five participants were females. The mean age was 23 years (S.D. = 6), and ages ranged from 18 to 55 years. All participants received a flat compensation of \$5 for participating in the experiment.

### **3.4.2 The CS task**

In the CS task used here, participants were first told that the amount of CO<sub>2</sub> in the atmosphere is affected by anthropogenic CO<sub>2</sub> emissions (emissions resulting from human activity) and natural processes that gradually absorb CO<sub>2</sub> from the atmosphere (for example, CO<sub>2</sub> is used by plant life and dissolves in the ocean). Furthermore, participants were shown the historic trend of CO<sub>2</sub> emissions and the resulting CO<sub>2</sub> concentration over a 150 year period from 1850 to 2000. They were also told that in the year 2000, the absorption of atmospheric CO<sub>2</sub> by natural processes was half of the CO<sub>2</sub> emissions. As a result, atmospheric CO<sub>2</sub> concentrations increased from preindustrial 1850 levels of about 600 GtC to about 769 GtC in 2000. Figure 3-1A shows the graphs with the historic trend given to the participants. Participants were also graphically shown a scenario in which the CO<sub>2</sub> concentration gradually rose to 938 GtC, about 22% higher than its year 2000 level, and then stabilized by the year 2100 (see Figure 3-1B). Participants were also provided a separate graph showing CO<sub>2</sub> emissions from 1900-2000 and CO<sub>2</sub> absorption from the atmosphere in 2000. They were then asked to sketch the likely future CO<sub>2</sub> absorption and emissions between 2001-2100 that corresponded to the CO<sub>2</sub> concentration scenario in Figure 3-1B. Finally, participants were asked to clearly explain the reasons for which they drew their CO<sub>2</sub> absorption and emissions.

The 938 GtC stabilization value in Figure 3-1B was taken from the IPCC's Fourth Assessment Report (FAR), which considers 938 GtC (= 450 ppmv) to be a realistically attainable

climate goal for the future (IPCC, 2007). Obviously, the objective in the CS task was not to test a participant's knowledge of future CO<sub>2</sub> emissions and absorption (which no one really knows), or to make predictions on the future trends (as climate scientists would do). Rather, the goal in the task was to test whether or not participants' CO<sub>2</sub> emissions and absorption responses reflect misconception from relying on the correlation heuristic or violating mass balance.

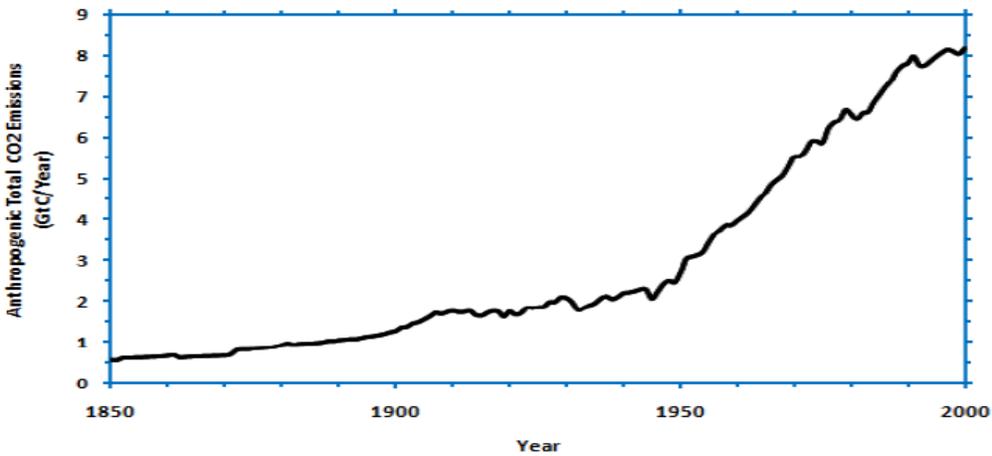


Figure 1. Total CO<sub>2</sub> emissions resulting from human activity (billion tons of carbon per year)

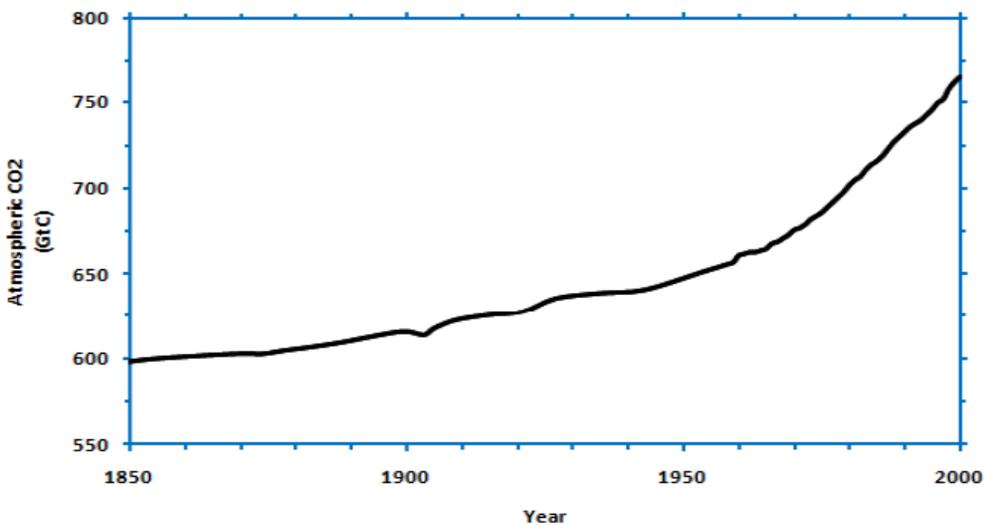
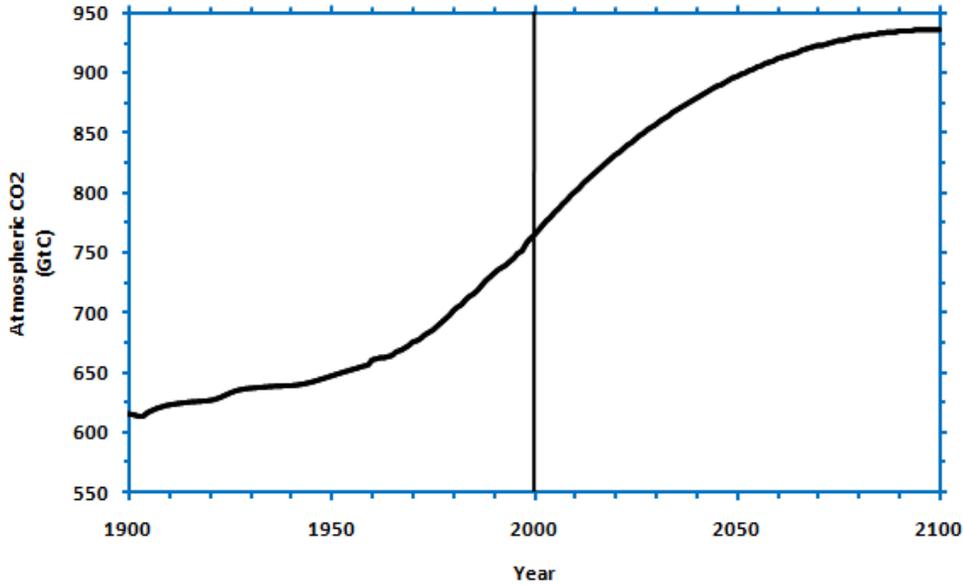


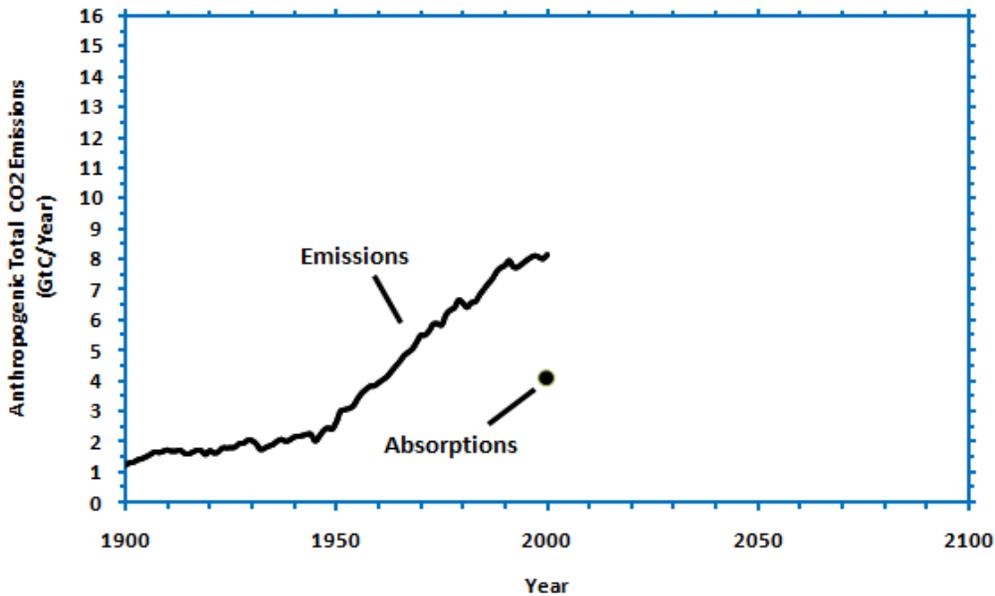
Figure 2. Atmospheric CO<sub>2</sub> concentrations (billion tons of carbon)

Figure 3-1 (A). Figures given to participants as part of the instructions in the CS task.



**Figure 3-1 (B). The trajectory of CO<sub>2</sub> concentration given to participants over a 200 year period (from 1900 to 2100).**

3.1(C)



**Figure 3-1(C). Participants had to sketch the trajectory of CO<sub>2</sub> absorptions and emissions corresponding to the trajectory of CO<sub>2</sub> concentration given in Figure 3-1(B).**

The CS task used in this paper is identical to the one used by Sterman and Booth Sweeney (2007) and Sterman (2008) with one minor difference: In their task, the “Anthropogenic CO<sub>2</sub>

emissions” and “net removals” (i.e., the inflow and outflow) were provided to participants in units of GtC/year and the CO<sub>2</sub> concentration in units of ppmv; whereas, we consistently use GtC for CO<sub>2</sub> concentration and GtC/year for CO<sub>2</sub> emissions and absorption.<sup>11</sup> The different units of measurement used to define the flows and stock by Sterman and Booth Sweeney (2007) could be somewhat responsible for any misconceptions about the relationship between the concentration and its associated flows. Participants may likely infer that the CO<sub>2</sub> concentration is unrelated to CO<sub>2</sub> emissions and absorption. The other option was to express CO<sub>2</sub> concentration in ppmv and the “Anthropogenic CO<sub>2</sub> emissions” and “net removals” in ppmv/year.<sup>12</sup>

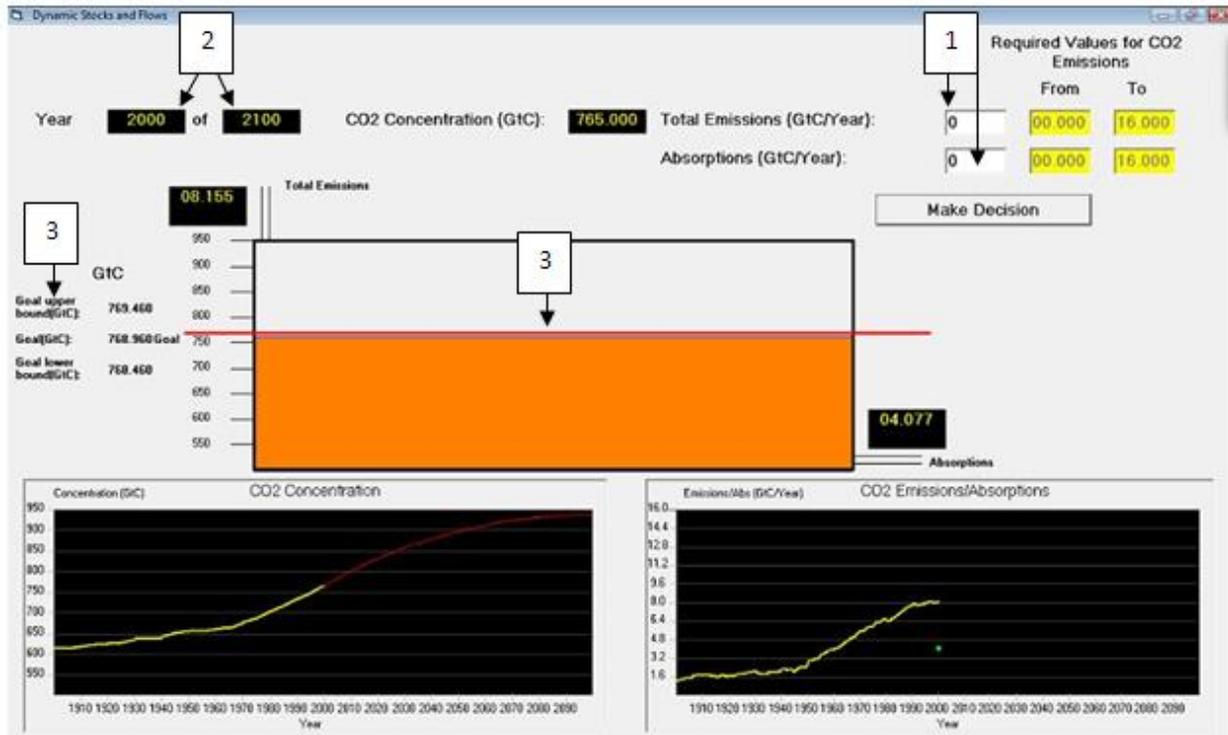
### **3.4.3 Dynamic Climate Change Simulator (DCCS)**

DCCS was developed based on previous research with generic stock-and-flows control tasks (Gonzalez & Dutt, in press). The simulation, its validation, and full functions are explained in different publications (Dutt & Gonzalez, 2009, 2011). For the purpose of the current research, we created the same CO<sub>2</sub> concentration scenario in DCCS as that depicted in the CS task. In DCCS, people made CO<sub>2</sub> emissions and absorption decisions each simulated year and got feedback on how their decisions effected the CO<sub>2</sub> concentration (see Figure 3-2).

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<sup>11</sup> GtC/year = 10<sup>9</sup> tons of Carbon / year or billion tons of Carbon / year and ppmv = parts per million by volume.

<sup>12</sup> 2.08 GtC = 1 ppmv using the method suggested by (CDIAC, 2009, <http://cdiac.ornl.gov/pns/faq.html> )



**Figure 3-2. The Dynamic Climate Change Simulation (DCCS).**

Participants made decisions by entering values for CO<sub>2</sub> emissions and absorption (number 1) during each simulated year from 2001 to 2100 (number 2) by clicking the "Make Decision" button. The task needed participants to enter CO<sub>2</sub> emissions and absorption so that the resultant CO<sub>2</sub> concentration would closely follow the CO<sub>2</sub> concentration scenario (shown in Figure 3-2) for every year until the year 2100. The yearly value of the CO<sub>2</sub> concentration goal was derived from the concentration scenario and was displayed as a red line on the atmospheric tank (number 3). The values of the upper and lower bound of the annual goal were displayed on the left hand side of the tank and an acceptable range of  $\pm 0.5$  GtC was assumed around it. The  $\pm 0.5$  GtC range was taken from Sterman and Booth Sweeney (2007) as a reasonable difference between CO<sub>2</sub> emissions and absorption for which the concentration was assumed to be stabilized at a yearly goal value. This range also helped us to classify participants according to whether or not their yearly CO<sub>2</sub> emissions and absorption decisions violated mass balance.

### 3.4.4 Violating mass balance and relying on correlation heuristic

The climate problem presented in the CS task and DCCS has a simple structure with one CO<sub>2</sub> concentration, one CO<sub>2</sub> emissions inflow, and one absorption outflow. CO<sub>2</sub> emissions add to the existing CO<sub>2</sub> concentration each year and CO<sub>2</sub> absorption subtracts from it. When CO<sub>2</sub> emissions are more than absorption, the concentration increases; and when CO<sub>2</sub> emissions are less than absorption, the concentration decreases. Given that CO<sub>2</sub> absorption are half of CO<sub>2</sub> emissions at the start of the CS task and DCCS (year 2000), the concentration is increasing. In order to stabilize the concentration at 938 GtC in 2100, one needs to keep emissions above absorption before 2100 (although with a diminishing gap between the two over time), and equalize emissions and absorption in 2100. A participant's response that does not satisfy the two previous constraints violates mass balance. To classify participants as violating mass balance, we visually determined whether or not a CO<sub>2</sub> emissions trajectory was greater than the CO<sub>2</sub> absorption trajectory before year 2100; and if emissions were less than or equal to  $\pm 0.5$  GtC/year away from absorption in 2100. If either of these two conditions was not met, a participant's response was classified as violating mass balance. Two independent raters that were blind to the hypotheses under test evaluated participants' sketched CO<sub>2</sub> emissions and absorption in both the CS task and DCCS. The inter-rater reliability statistic for the two independent raters was Kappa = 0.85 ( $p < 0.001$ ), 95% CI (0.80, 0.90). This Kappa statistic reveals a satisfactory level of agreement between the two raters (Landis & Koch, 1977).

To determine participants' reliance on the correlation heuristic, we correlated their CO<sub>2</sub> emission values over a 100 year period (between years 2001 and 2100) to their CO<sub>2</sub> concentration values over the same period in both the CS task and DCCS. We assumed a very conservative threshold of 0.8 for the correlation coefficient value as classifying participants'

responses as relying on the correlation heuristic. Furthermore, their responses rely on the correlation heuristic if CO<sub>2</sub> emissions in 2100 are greater than 11.51 GtC/year. The value of 11.51 GtC/year was taken to be the largest of the average CO<sub>2</sub> emissions entered by participants in the CS task and DCCS. To find the mean emissions, we separately averaged the CO<sub>2</sub> emissions values entered or sketched by participants in different tasks over a 100 year period. Thus, a participant's response was classified as relying on the correlation heuristic if the correlation coefficient between their CO<sub>2</sub> emissions and CO<sub>2</sub> concentration trajectory over a 100 year period was more than 0.8; and if their CO<sub>2</sub> emissions in the year 2100 exceeded 11.51 GtC/year.

### **3.4.5 Experiment's Design and Dependent Measures**

Participants were randomly assigned to one of the two between-subjects conditions: *description* or *experience*. In the *description* condition, participants were asked to do only the paper-and-pencil CS task. In the *experience* condition, participants performed the DCCS task first and then did the CS task. The CS task was given to participants in both conditions because it constitutes the main testing phase, which allowed us to evaluate their reliance on the correlation heuristic and violation of mass balance with or without DCCS experience. We wanted to evaluate the influence of two independent measures in this experiment: the experience in DCCS (present in *experience* condition and absent in *description* condition) and the participants' backgrounds (STEM or non-STEM).

To test H1, we compared participants' reliance on the correlation heuristic and their violation of mass balance in the CS task across the *experience* and *description* conditions. To test H2, we first explored correlation heuristic reliance and mass balance violations among STEM and non-STEM backgrounds between the CS task in the *experience* and *description* conditions.

Then, we explored correlation heuristic reliance and mass balance violations between STEM and non-STEM backgrounds within the CS task in the *description* condition, and within DCCS and the CS task in the *experience* condition. Later, we also coded and analyzed participants' explanations about the reasoning and procedure they followed while sketching CO<sub>2</sub> emissions and absorption.

### **3.4.6 Procedure**

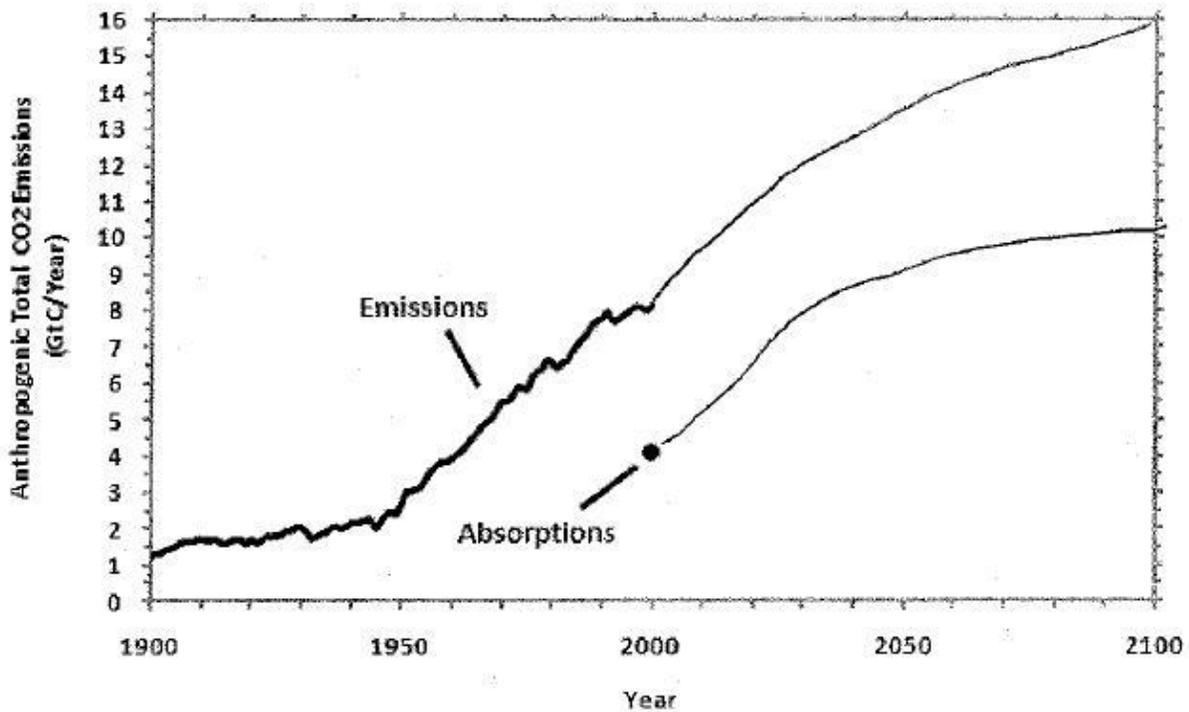
In the *description* condition, participants were first asked to read the instructions as part of the CS task and the experimenter answered participants' questions at this point, if any. Participants were not given any details on how they could solve the task correctly, only clarification questions in instructions were answered. Then, they were asked to sketch the CO<sub>2</sub> emissions and absorption over the 100 year period. No participant took more than 15 minutes on the CS task in either the *description* or *experience* conditions. In order to equalize the length of the *description* and *experience* conditions, participants in the *description* condition were given an unrelated task at the beginning of their experiment.

Participants assigned to the *experience* condition were first asked to read the instructions that appeared on a computer screen before they could start in DCCS. The experimenter then answered any questions clarifying the instructions, if any. Participants were told that after DCCS, they would be asked to respond to a short paper-and-pencil task. But they were not shown the CS task at that time. Once participants finished the DCCS, they were handed the CS task immediately after.

### 3.5 Results

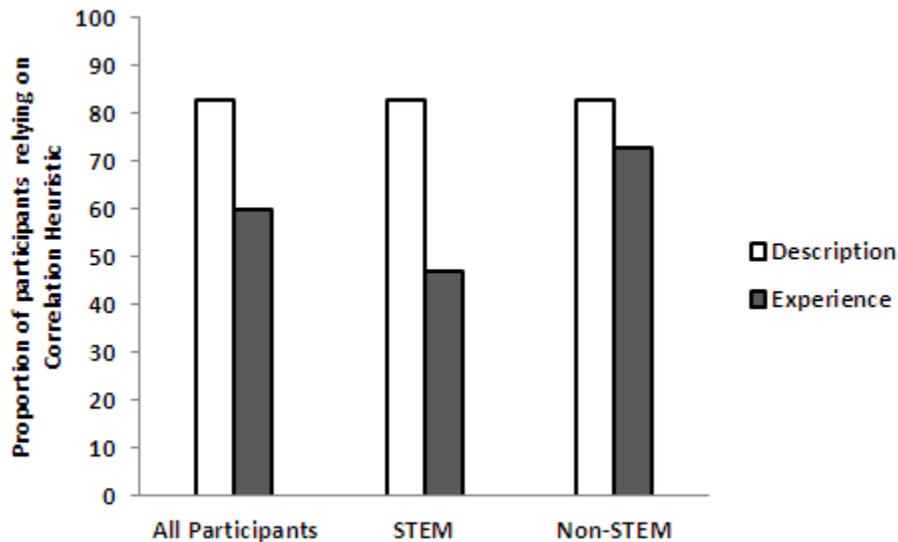
#### 3.5.1 Misconceptions across Description and Experience

Misconceptions were analyzed by first considering the percentage of participants that relied on the correlation heuristic and violated mass balance. Figure 3-3 shows the response of a typical participant in the *description* condition. For this participant, CO<sub>2</sub> emissions exceed absorption by a large difference in the year 2100, which violates mass balance. Furthermore, the shape of the CO<sub>2</sub> emissions curve is highly correlated to the shape of the CO<sub>2</sub> concentration trajectory given in the problem, showing the participant's reliance on the correlation heuristic. Therefore, by responding with the shapes of CO<sub>2</sub> emissions and absorption curves in Figure 3-3, this participant relies on the correlation heuristic and violates mass balance.



**Figure 3-3. A typical sketch by a non-STEM participant in the *description* condition. The participant makes CO<sub>2</sub> emissions much greater than CO<sub>2</sub> absorptions in the year 2100. The trajectory of CO<sub>2</sub> emissions shape is correlated and similar to CO<sub>2</sub> goal trajectory that was given to the participant as part of the instructions. The gap between the emissions and absorptions is more than  $\pm 0.5$  GtC/year in the figure.**

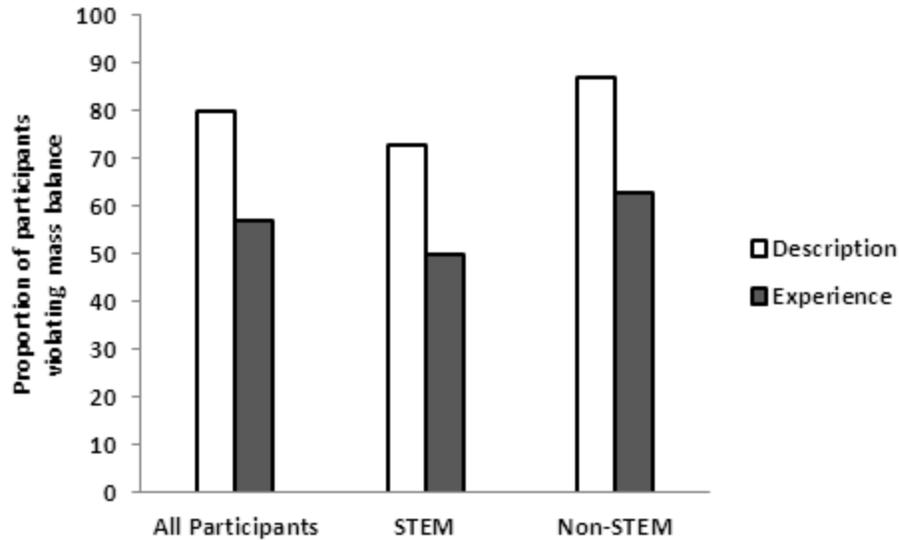
Figure 3-4 shows the proportion of participants relying on the correlation heuristic in the CS task in the *experience* and *description* conditions. The aggregated result is further divided by STEM and non-STEM participants. Overall, 82% of participants relied on the correlation heuristic in the *description* condition, while 60% of participants did so in the CS task in the *experience* condition ( $\chi^2(1) = 6.82, p < .01, r^{13} = .24$ ). This finding rejects hypothesis H1.



**Figure 3-4. Proportion of participants relying on correlation heuristic in the CS task in the *description* and *experience* conditions. The figure also shows the breakup of correlation heuristic for STEM and non-STEM backgrounds.**

Figure 3-5 shows the proportion of participants violating mass balance in the CS task in the *experience* and *description* conditions. The aggregated result is further divided by STEM and non-STEM participants. Overall, 80% of the participants violated mass balance in the *description* condition, while 57% did so in the CS task in the *experience* condition ( $\chi^2(1) = 7.55, p < .01, r = .51$ ). Again, this finding rejects hypothesis H1.

<sup>13</sup> This refers to the effect size unless otherwise mentioned.



**Figure 3-5. Proportion of participants violating mass balance in the CS task in the *description* and *experience* conditions. The figure also shows the breakup of participants violating mass balance within STEM and non-STEM backgrounds.**

In order to understand the reasons why participants violate the principle of mass balance, we broke results into constituting subparts as shown in Table 3-1: Net CO<sub>2</sub> emissions in 2100 > 0.5 GtC/year, Net CO<sub>2</sub> emissions in 2100 < 0.5 GtC/year, and Net CO<sub>2</sub> emissions in 2100 between ±0.5 GtC/year. The Net CO<sub>2</sub> emissions in 2100 (denoted by the short form “NET E”) equals CO<sub>2</sub> emissions minus the absorption in the same year. In order not to violate mass balance, the NET E should ideally be equal to 0 GtC/year because participants were asked to stabilize the CO<sub>2</sub> concentration in 2100. The assumption of ± 0.5 GtC/year in Table 3-1 serves as a less stringent for participants. Thus, a participant’s NET E could be as high as 0.5 GtC/year or as low as -0.5 GtC/year and still would not be classified as violating mass balance. The Average Absolute NET E refers to the positive value of Average Net CO<sub>2</sub> emissions in 2100 (where the averaged is taken over all participants in the respective condition). “VOMB?” refers to the proportion of participants violating mass balance.

As seen in Table 3-1, 80% (N=48/60) of participants in the *description* condition wrongly inferred that CO<sub>2</sub> emissions could be either greater than or less than CO<sub>2</sub> absorption and the CO<sub>2</sub> concentration still could be stabilized in 2100 (column labeled: “Net E > 0.5 or Net E < -0.5”); whereas, in the *experience* condition, 57% (N=34/60) and 26% (N=16/60) of participants demonstrated the same incorrect inference in the CS task ( $\chi^2(1) = 11.63, p < .001, r = .31$ ) and in DCCS ( $\chi^2(1) = 43.25, p < .001, r = .49$ ), respectively. Similarly, 78% (N=47/60) of participants wrongly inferred that CO<sub>2</sub> emissions could exceed CO<sub>2</sub> absorption and the CO<sub>2</sub> concentration could still be stabilized in 2100 (column labeled: “Net E > 0.5”) in the *description* condition; whereas, in the *experience* condition, 50% (N=30/60) and 18% (N=11/60) of participants showed this wrong inference in the CS task ( $\chi^2(1) = 11.63, p < .001, r = .31$ ) and in DCCS ( $\chi^2(1) = 43.25, p < .001, r = .49$ ), respectively.

Finally, participants in the CS task and DCCS (*experience* condition) had a significantly smaller Average Absolute Net E in the year 2100 compared to participants in the *description* condition ( $U = 1133.00, Z = -3.536, p < .001, r = -.32$  and  $U = 542.50, Z = -6.772, p < .001, r = -.62$ , respectively). Thus, the experience gained in DCCS helped participants to reduce mass balance violations. Furthermore, the reduction helped participants to perform better in the following CS task in the *experience* condition compared to that in the *description* condition.

Altogether, participants in the *experience* condition showed fewer misconceptions (i.e., less reliance on the correlation heuristic and less violation of mass balance) in the CS task in the *experience* condition compared to those in the CS task in the *description* condition.

**Table 3-1. Conservation of Mass Balance and Conformance.**

Task	Average Absolute NET E	Net CO <sub>2</sub> emissions in 2100 (called "NET E") = CO <sub>2</sub> emissions - absorptions in 2100 (GtC/year)									
		Net E > 0.5 (A)		Net E ≥ -0.5 and Net E ≤ 0.5		Net E < -0.5 (B)		Net E > 0.5 or Net E < -0.5 (A) + (B)		VOMB?	
		N	%	N	%	N	%	N	%	N	%
CS (description)	5.40 (3.76)	47	78	12	20	01	02	48	80	48	80
CS (experience)	2.93 (3.37)	30	50	26	43	04	07	34	57	34	57
DCCS (experience)	0.66 (1.58)	11	18	44	73	05	08	16	26	18	30
CS (description, STEM)	4.63 (3.63)	21	70	08	27	01	03	22	73	22	73
CS (description, non-STEM)	6.21 (3.77)	26	87	04	13	00	00	26	87	26	87
CS (experience, STEM)	2.18 (2.77)	12	40	11	37	07	23	19	63	15	50
CS (experience, non-STEM)	3.68 (3.78)	18	60	11	37	01	03	19	63	19	63
DCCS (experience, STEM)	0.56 (1.16)	06	20	21	70	03	10	09	30	09	30
DCCS (experience, non-STEM)	0.77 (1.93)	05	17	23	77	02	07	07	23	09	30

Note: Net CO<sub>2</sub> emissions in 2100 (called "Net E") = CO<sub>2</sub> emissions in 2100 – CO<sub>2</sub> absorptions in 2100 and should be ideally equal to 0 GtC/year. Average Absolute Net E = | Average CO<sub>2</sub> emissions in 2100 – Average CO<sub>2</sub> absorptions in 2100 | when the different values are averaged over all participants in a specific task. Net E > 0.5; Net E ≥ -0.5 and Net E ≤ 0.5; and, Net E < -0.5 refer to when the Net CO<sub>2</sub> emissions in year 2100 were greater than 0.5, in-between -0.5 and 0.5, or less than -0.5 GtC/year. The value of 0.5 GtC/year is the same as used by Sterman and Booth Sweeney (2007). The assumption of ±0.5 GtC/year makes the requirement on Net CO<sub>2</sub> emissions in 2100 to equal 0, to be less stringent for participants. Thus, a participant's Net CO<sub>2</sub> emissions in 2100 could be as high as 0.5 GtC/year or as low as -0.5 GtC/year and still she would not commit violation of mass balance. "VOMB?" refers to the proportion of participants that violate mass balance, i.e., whether or not CO<sub>2</sub> emissions > absorptions before year 2100, and, Net CO<sub>2</sub> emissions in 2100 < 0.5 GtC/year. A value in round brackets, "()", indicates the standard deviation around the average value.

### 3.5.2 Interaction between Background and Condition

With the additional factor of participants from both STEM and non-STEM backgrounds, DCCS' exact influence in the *experience* condition become becomes difficult to untangle if there are significant interactions between participants' backgrounds and the condition given. As the main effect of experience in DCCS significantly reduced reliance on the correlation heuristic and violation of mass balance in the CS task in the *experience* condition, we investigated the effects of DCCS's experience among both STEM and non-STEM backgrounds. There was a significant interaction between the condition (*experience* or *description*) in the CS task and participants' backgrounds (STEM or non-STEM) for reliance on the correlation heuristic ( $F(1, 116) = 3.6, p < .05$ ). As shown in Figure 3-4, the difference in reliance between the CS task in the *description* and *experience* conditions is greater for STEM participants (36%) than for non-STEM participants (10%). This difference was significant for STEMs (CS task, *description* (83%) > CS task, *experience* (47%) with  $\chi^2(1) = 8.86, p < .001, r = .38$ ), but not for non-STEMs (CS task, *description* (83%) = CS task, *experience* (73%) with  $\chi^2(1) = 0.37, ns, r = .08$ ).

The interaction between condition (*experience* or *description*) in the CS task and backgrounds (STEM or non-STEM) for violating mass balance was not significant ( $F(1, 116) = 0.0, ns$ ). As shown in Figure 3-5, DCCS experience led to a reduction in mass balance violations for both STEMs and non-STEMs. Therefore, as Figure 3-5 and Table 3-1 indicate, the experience gained in DCCS (*experience* condition) reduced violation of mass balance for both STEMs (23%) and non-STEMs (24%). These differences were significant for both backgrounds: for STEMs, 73% in *description* condition > 50% in *experience* condition with  $\chi^2(1) = 3.50, p <$

.05,  $r = .24$ ; and for non-STEMs, 87% in *description* condition > 63% in *experience* condition with  $\chi^2(1) = 4.36, p < .05, r = .27$ .

### **3.5.3 Misconceptions among STEMs and non-STEMs (Investigating hypothesis H2)**

We compared the proportion of misconceptions between STEM and non-STEM participants within the CS task in the *description* and *experience* conditions (hypothesis H2). In the *description* condition's CS task, we found an excessive reliance on the correlation heuristic by both STEMs (83%) and non-STEMs (83%), and the difference between these groups was not significant ( $\chi^2(1) = 0.11, ns, r = .04$ ) (see Figure 3-4). Similarly, as seen in Figure 3-5, the difference between STEMs (73%) and non-STEMs (87%) for violating mass balance in the CS task in the *description* condition was not significant ( $\chi^2(1) = 1.67, ns, r = .17$ ). These results replicate Serman's (2008) and Serman and Booth Sweeney's (2007) findings. In contrast in the *experience* condition's CS task, the difference in correlation heuristic reliance between STEMs (47%) and non-STEMs (73%) was significant ( $\chi^2(1) = 4.44, p < .05, r = .27$ ) (see Figure 3-4), but the difference between STEMs (50%) and non-STEMs (63%) for violating mass balance was not ( $\chi^2(1) = 1.09, ns, r = .14$ ) (see Figure 3-5).

Some of the reasons for the lack of differences between STEMs and non-STEMs on violating mass balance can be seen in Table 3-1. For example, STEMs and non-STEMs were equally likely to infer that the CO<sub>2</sub> concentration could be stabilized even when emissions do not equal the absorption in 2100 in the CS task in both conditions (CS task, *description*: 27% versus 13% with  $\chi^2(1) = 2.46, ns, r = .20$ ; CS task, *experience*: 37% versus 37% with  $\chi^2(1) = 3.27, ns, r = .23$ ). Furthermore, STEMs and non-STEMs were equally likely to infer that CO<sub>2</sub> emissions

could exceed absorption and the CO<sub>2</sub> concentration could still be stabilized in 2100 in both conditions (column labeled: “Net E > 0.5”) (CS task, *description*: 70% versus 87% with  $\chi^2(1) = 2.46$ , *ns*,  $r = .20$ ; CS task, *experience*: 40% versus 60% with  $\chi^2(1) = 3.27$ , *ns*,  $r = .23$ ). Finally, there were no significant differences between STEMs and non-STEMs in the Average Absolute Net E in the *experience* and *description* conditions (CS task, *description*:  $U = 357.50$ ,  $Z = -1.372$ , *ns*,  $r = -.17$ ; CS task, *experience*:  $U = 343.00$ ,  $Z = -1.623$ , *ns*,  $r = -.21$ ).

### 3.5.4 Participants' Explanations

As mentioned above, all participants were asked to explain the reason for which they drew the absorption and CO<sub>2</sub> emissions for the given CO<sub>2</sub> concentration trajectory that they did. These explanations help us to investigate participants' existing mental models. Sterman and Booth Sweeney (2007) had previously analyzed participants' written explanations and we coded our participants' written explanations according to the same procedure they detailed. Explanations were classified under the following categories, which we also used: Mass Balance, Correlation Heuristic, Inertia/Delays, CO<sub>2</sub> Fertilization, Sink Saturation, and Technology. The definitions and explanations of these categories are provided under each category in Table 3-2. Mass balance indicated awareness of a relationship between CO<sub>2</sub> emissions/absorption flows and the concentration of atmospheric CO<sub>2</sub> (i.e., where participants wrote terms such as “mass balance”).

**Table 3-2. Codes for written participant explanations in CS tasks (*experience, description*) based on rater Kappa statistics.**

Categories <sup>1</sup>	CS ( <i>description</i> ) <sup>2</sup>		CS ( <i>experience</i> ) <sup>2</sup>	
	N <sup>3</sup>	% <sup>4</sup>	N <sup>3</sup>	% <sup>4</sup>
<i>Mass Balance</i>				
Description indicating awareness of relationship between emission and absorption flows and the concentration of atmospheric CO <sub>2</sub> ; terms such as mass balance.	20	33	29	48
STEM	15	50	16	52
Non-STEM	05	17	13	45
<i>Correlation Heuristic</i>				
Description mentioning correlations or similarity of behavior or patterns among emissions, atmospheric CO <sub>2</sub> , indication that emissions change should be proportional to changes in atmospheric CO <sub>2</sub> (perhaps with lags or time delays).	39	65	22	37
STEM	15	50	10	32
Non-STEM	24	80	12	41
<i>Inertia/Delays</i>				
Mention of delays in response of system to changes in emissions, atmospheric CO <sub>2</sub> ; terms such as ‘delay,’ ‘lag,’ ‘inertia,’ etc.	10	17	03	05
STEM	05	17	02	06
Non-STEM	05	17	01	03
<i>CO<sub>2</sub> Fertilization</i>				
Mention of the possibility that CO <sub>2</sub> absorptions may rise due to enhanced plant growth, other effects of higher atmospheric CO <sub>2</sub> or higher temperatures.	17	28	04	07
STEM	09	30	01	03
Non-STEM	08	27	03	10
<i>Sink Saturation</i>				
Mention of the possibility that CO <sub>2</sub> absorptions may fall due to Carbon sink saturation, e.g., deforestation, ocean saturation, carbon discharge stimulated by higher.	10	17	05	08
STEM	04	13	00	00
Non-STEM	06	20	05	17
<i>Technology</i>				
Indicates inference that technology will enable emissions reductions (e.g., alternative energy sources) or enhance CO <sub>2</sub> absorptions (e.g., anthropogenic carbon capture and sequestration).	06	12	04	08
STEM	05	17	02	06
Non-STEM	01	07	02	10

*Note:* <sup>1</sup> Categories and their definitions were taken from Sterman and Booth Sweeney (2007). A single participant's explanation could be classified into multiple categories. Also, absence of a category in a participant written explanation does not reveal whether or not the participant was aware of it. Even if the participant's conclusion was wrong but belonged to a particular category, it was classified as part of that category. <sup>2</sup> The CS task (*description*) and CS task (*experience*) were given in the *description* and *experience* conditions of the experiment respectively. <sup>3</sup> N refers to the number of participants whose explanation included the category under consideration. <sup>4</sup> % proportion of participant's explanation out of a total of 60 participants in the CS task (*description*) and 60 participants in the CS task (*experience*).

Correlation Heuristic indicated the incorrect assumption that emissions changes should be proportional to changes in atmospheric CO<sub>2</sub> (perhaps with lags or time delays). Inertia/Delays indicated mention of delays in response of system to changes in emissions, atmospheric CO<sub>2</sub>, and the use of terms such as "delay," "lag," "inertia," etc. CO<sub>2</sub> Fertilization indicated the possibility that CO<sub>2</sub> absorption may increase due to enhanced plant growth and other effects of greater atmospheric CO<sub>2</sub> or temperatures. Sink Saturation indicated the possibility that CO<sub>2</sub> absorption may fall due to saturation of carbon sinks (e.g., oceans). Finally, Technology indicated the assumption that technology will more easily enable CO<sub>2</sub> emissions reductions (e.g., alternative energy sources) or enhance CO<sub>2</sub> absorption (e.g., anthropogenic carbon capture and sequestration).

Two independent raters, who were blind to the hypotheses under test, coded participant explanations. The inter-rater reliability statistics for the two independent raters was Kappa, Mass Balance = 0.95 ( $p < 0.001$ ), 95% CI (0.89, 1.00); Kappa, Correlation Heuristic = 0.97 ( $p < 0.001$ ), 95% CI (0.92, 1.00); Kappa, Inertia = 1.00 ( $p < .001$ ), 95% CI (1.00, 1.00); Kappa, CO<sub>2</sub> Fertilization = 0.91 ( $p < 0.001$ ), 95% CI (0.81, 1.00); Kappa, Sink Saturation = 0.92 ( $p < 0.001$ ), 95% CI (0.81, 1.00); and Kappa, Technology = 0.91 ( $p < 0.001$ ), 95% CI (0.78, 1.00). These Kappa statistics reveal a satisfactory level of agreement between the two raters on their individual categorizations (Landis & Koch, 1977), hence the same levels of categorization was used for subsequent analysis of participant explanations (any disagreements between raters were resolved by meeting and active discussion). Table 3-2 displays the frequency and proportions of explanations for the CS task in the *description* and *experience* conditions, then further broken down by participants' backgrounds. A participant's explanation could belong to more than one category at the same time.

The differences between explanations in the *description* and *experience* conditions for the Mass Balance, Inertia/Delays, Sink Saturation, and Technology categories were insignificant ( $\chi^2(1) = 2.79, ns, r = .15$ ;  $\chi^2(1) = 4.23, ns, r = .19$ ;  $\chi^2(1) = 1.91, ns, r = .13$ ;  $\chi^2(1) = 0.37, ns, r = .06$  respectively). The proportion of participants suggesting Correlation Heuristic in their explanations, however, was significantly lower in the *experience* than in the *description* condition (37% versus 65%;  $\chi^2(1) = 9.64, p < .01, r = .28$ ). The proportion of explanations suggesting an increase in CO<sub>2</sub> absorption due to CO<sub>2</sub> Fertilization was also significantly larger in the *description* than in the *experience* condition (28% versus 7%;  $\chi^2(1) = 9.76, p < .01, r = .29$ ). The latter two differences consistently show why participants suffered from greater misconceptions in the *description* condition than in the *experience* condition.

The difference between the *description* and *experience* conditions in the proportion of Correlation Heuristic explanations was among non-STEMs, but not STEMs (non-STEM 80% to 41%;  $\chi^2(1) = 9.25, p < .001, r = .40$ ; STEM 50% to 32%;  $\chi^2(1) = 1.98, ns, r = .18$ ). On the other hand, the difference between the *description* and *experience* conditions for CO<sub>2</sub> Fertilization explanations was a result found among STEMs and non-STEMs (STEM 30% to 3%;  $\chi^2(1) = 7.97, p < .01, r = .36$ ; non-STEM 27% to 10%;  $\chi^2(1) = 2.59, ns, r = .21$ ). Therefore, there was an increase in the Correlation Heuristic explanations from the *description* to the *experience* conditions for non-STEMs; whereas, there was a reduction in CO<sub>2</sub> Fertilization explanations from the *description* to the *experience* condition for STEMs.

Finally, if STEMs demonstrated fewer misconceptions with their Correlation Heuristic and Mass Balance responses than non-STEMs, there should be significant differences in these two categories within the *description* condition between the types of backgrounds. Moreover, if DCCS is an effective manipulation, then the proportions of Correlation Heuristic and Mass

Balance explanations should be less and more respectively for both STEMs and non-STEMs in the *experience* condition. We tested for these expectations. In the *description* condition, the proportion of Mass Balance explanations made by STEMs were significantly larger than those made by non-STEMs, and the proportion of Correlation Heuristic explanations were significantly less for STEMs than for non-STEMs (50% versus 17% with  $\chi^2(1) = 7.50, p < .01, r = .35$ ; 50% versus 80% with  $\chi^2(1) = 5.93, p < .05, r = .31$  respectively). In the *experience* condition, however, differences in the use of both categories were insignificant between STEMs and non-STEMs (52% and 45% with  $\chi^2(1) = 0.28, ns, r = .07$ ; 32% and 41% with  $\chi^2(1) = 0.54, ns, r = .10$ ). These results highlight the fact that STEMs showed fewer misconceptions in their explanations than non-STEMs in the *description* condition, but not in the *experience* condition.

### **3.6 Discussion and conclusions**

One main and consistent result of our study is that acquiring experiential feedback in the Dynamic Climate Change Simulator (DCCS) helps to reduce participants' misconceptions about the way the climate system in the subsequent Climate Stabilization (CS) task works. Reducing misconceptions about Earth's climate is likely to reduce wait-and-see behavior (Bostrom et al., 1994; Sterman, 2008; Sterman & Booth Sweeney, 2002, 2007).

Feedback in DCCS enables participants to test several hypotheses they might have about how CO<sub>2</sub> emissions and absorption processes affect the CO<sub>2</sub> concentration. It is likely that the ability to test several hypotheses repeatedly about the cause-and-effect relationship in DCCS enables them to understand that the concentration increases when CO<sub>2</sub> emissions are greater than absorption, decreases when emissions are less than absorption, and stabilizes at a particular value when emissions equal absorption. Consequently, participants are able to apply this understanding in the following CS task. We do find some evidence for this reasoning from our results. For

example, the proportion of participants' explanations indicating the correlation heuristic was far less in the *experience* condition's CS task than that in the *description* condition. Therefore, it seems that the experience gained in DCCS enabled participants to decrease their reliance on the correlation heuristic and also enabled them to improve their performance in the CS task that followed.

The above explanations are also supported by similar findings in the literature for other dynamic tasks (Cronin et al., 2009; Dutt & Gonzalez, 2011; Gonzalez, Lerch, & Lebiere, 2003; Moxnes & Saysel, 2009). For example, Cronin et al. (2009) suggest that participants can get increasingly accurate answers in simple dynamic tasks with even just "correct/incorrect" feedback given after each attempt. In the first attempt, only 15% of their participants answered the accumulation question correct, but 80% of the participants were able to solve the problem correctly by the seventh attempt. Similarly, it appears that participants in our study are able to successfully transfer their experiences through repeated feedback in DCCS to the following CS task. Based upon the success of using DCCS, the use of experiential tools (like DCCS) are recommended to aid in the process of formulating climate policies. Considering the reduction in correlation heuristic reliance and mass balance violations with experience after DCCS, another important implication is the use of DCCS as a tool to supplement basic education about climate change at all levels of schooling.

However, we also found differential effects of using DCCS for participants with science (STEM) and non-science (non-STEM) backgrounds in our results: the decrease in correlation heuristic reliance between the CS task in the *description* and *experience* conditions was present for STEMs but absent for non-STEMs. Given that neither STEMs or non-STEMs relied on the correlation heuristic during DCCS, what we can conclude is that only STEMs were able to retain

and transfer the experiential knowledge previously acquired to the following CS task. In contrast, non-STEMs reduced their reliance on the correlation heuristic after performing in DCCS, but this reduction was not seen in non-STEMs in the *description* condition. One probable reason is that STEMs are more commonly exposed to dynamic problems that require attaining an equilibrium or control of an accumulation as part of their prior training and curriculum. For example, science courses in thermodynamics and physics cover concepts of mass balance and energy balance as part of their curriculum. When STEMs are asked to perform in DCCS, they are likely reminded of these equilibrium concepts that they previously learnt as part of their prior education. This background might enable STEMs do better in the following CS task compared to those that did not gain experience in DCCS. On the other hand, courses in the humanities and social sciences do not explicitly cover concepts of mass balance and energy balance as part of their curriculum. Thus, non-STEMs may not necessarily have the prior knowledge base to rely on. As learning new concepts might take time, non-STEMs are unlikely to be able to carry forward these concepts and do better in the following CS task.

One could also argue that the reduction in correlation heuristic reliance among STEMs may also be due to their prior education in mathematics and sciences that help these participants see the underlying stock-and-flow structure of the problem (Chi et al., 1981).<sup>14</sup> STEMs may be able to recognize the stock-and-flow structure and how the associated flows (CO<sub>2</sub> emissions and absorption) affect the CO<sub>2</sub> concentration. This explanation is supported by prior research, which has shown that people with expertise in mathematics and sciences can learn faster and generate more meaningful categories, superior performance, better use of problem metaphors, and a deeper understanding of the problem structure compared to people without the same expertise

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<sup>14</sup> By stock-and-flow structure we mean the ability to recognize the accumulation and its corresponding inflows and outflows, and to be able to determine how flow processes affect the accumulation in a problem.

(Chi et al., 1981; Schoenfeld, 1982). For example, Schoenfeld (1982) has shown that college freshmen students and college faculty members generate very different classifications for problems in geometry and algebra. College freshmen students classify these problems based upon surface similarities (e.g., based upon circles, functions, or whole numbers); whereas, college faculty members with prior experience show a deeper understanding of the problem structure in their classifications.

The fact that simulation tools have differential success based upon prior scientific background has some important implications. First, if experience needs the support of a mathematical background to reduce misconceptions as shown in our results, then it is possible that many policymakers, who lack the needed scientific training and mathematical backgrounds, might make climate policies while relying on the correlation heuristic. Second, the design of simulation tool (e.g., what features to put in these tools and the length of training in these tools etc.) needs to be carefully determined, given that they would be directed towards both students with and without prior STEM education. Although we can only speculate, perhaps it might be beneficial to extend the length of training for non-STEMs compared to STEMs; as extended practice with simulation tools might yield more benefits for non-STEMs.

Furthermore, we find that there is a reduction in the proportion of participants violating mass balance; however, there is still an absence of a corresponding increase in explanations indicating Mass Balance. This inconsistency between what people “do” versus what people “say” might be due to the previously recorded dissociation between explicit and implicit learning (Berry & Broadbent, 1984). People can speak English well (implicit learning) without being able to express a single rule of grammar (explicit learning). The absence of an increase in the proportion of Mass Balance explanations by participants (explicit learning) need not lead to a

decrease in the proportion of participants committing a violation of mass balance (implicit learning).

Finally, the problems used in DCCS and in the following CS task in this study were identical. Therefore, there is a possibility that any improvement in participants' performance in the CS task following DCCS is because of the similarity they perceive between these two tasks. Although this observation might not necessarily constitute a problem for the effectiveness of the DCCS manipulation, it does raise an important question for future research: whether people are learning the stock-and-flow structure of the problem while they are performing DCCS, or whether they are learning the numerical values of CO<sub>2</sub> emissions, absorption, and CO<sub>2</sub> concentration and these shapes over time only (i.e., the surface of the problem). As the participants' explanations in the CS task do show an overall reduction in their misconceptions about correlation heuristic in our results, DCCS is believed to affect the way participants observed the stock-and-flow structure in the problem. As part of future research, however, we would like design problems for the *experience* condition's CS task that are different from or similar to the one given in DCCS. By doing so, we will be able to test the boundaries of experiential learning in DCCS to similar or novel problems in the CS task. Second, we also plan to discuss misconceptions with participants after their performance in DCCS and before they complete the CS task. This second manipulation is likely to produce even stronger evidence of learning, and perhaps even more drastic reduction in people's misconceptions in the following CS task.

Although we all experience climate in our day-to-day lives, it is possible that we misperceive the association between our decisions and their effects because the climate effects are vastly delayed in time. There is an important need to develop efficient methods of climate

risk communication where methods are designed in accordance with people's existing mental models of climate change (Morgan et al., 2002). According to Morgan et al. (2002), simply asking experts what to do for the climate and then passing the expert's view onto lay people generally results in lay people missing the point and becoming confused, disinterested, and even annoyed. In a world where people with non-STEM backgrounds are plentiful and their support is clearly needed considering the global nature of the climate problem, the experts should understand and pay close attention to the underlying mental models, pre-existent knowledge, and needs of lay people. Again here, the use of simulation tools like DCCS is likely to help improve lay people's understanding of the cause-and-effect relationships that govern Earth's climate.

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### **3.8 Next Chapter's Highlights**

The next chapter discusses how a physical representation helps to reduce people's reliance on correlational thinking in different problems and contexts compared to other graphical and text representations that are commonly used. The use of physical representation is expected to reduce people's wait-and-see behavior on climate change.

## **Chapter 4: The Benefits of Using a Physical Representation**

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### **Reducing the Linear Perception of Nonlinearity: Use of a Physical Representation**

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## 4.1 Abstract

Research shows that while judging accumulations of quantities over time (e.g., money in a bank account or CO<sub>2</sub> in Earth's atmosphere), people assume that the shape of the accumulation is similar to the shape of the inflow (i.e., people rely on a correlation heuristic). Relying on correlation heuristic is particularly worrisome for Earth's climate as judging CO<sub>2</sub> accumulation according to its emissions (inflow) would underestimate the actual (nonlinear) increase in accumulation, undervaluing the seriousness of climate problem and resulting in wait-and-see behavior. We report two experiments where we test the effectiveness of a physical representation compared to graphical (mathematics graphs) and text representations in reducing people's underestimation of nonlinear accumulation in different contexts and problems. A physical representation presents an accumulation using a picture that works as a metaphor. In a first experiment, participants drew the shape of an accumulation over time relying on physical or graphical representations in one of two contexts: carbon-dioxide and marbles. Although participants underestimated the accumulation in both contexts, their underestimation was reduced in the physical representation compared to the graphical. In a second experiment, we extended the evaluation of physical representation against text and graphical representations in two different problems in the climate context (with linearly increasing or decreasing inflow). Again, the underestimation of accumulation was reduced in the physical representation compared to the other two representations, regardless of the nature of the problem. We discuss implications of using the physical representation for improving people's estimates of nonlinear CO<sub>2</sub> accumulation.

*Keywords:* linear thinking, climate change, physical representation, graphical representation, text representation, correlation heuristic

## 4.2 Introduction

Consider a fable that tells a story of an ancient king and the inventor of chess. When the inventor presented the chess game to the king, the king was so impressed that he offered him a reward. The inventor asked for rice grains for each square of the chess board, such that he would get one grain for the first square of the board, two for the second, four for the third, and so on (i.e.,  $2^{n-1}$ , where  $n$  is the square number starting at  $n = 1$ ). The king thought that the inventor was modest and accepted the proposal, but he realized halfway into the exercise how difficult it would be to meet the request. Assuming that 60 grains weigh 1 gram, meeting the inventor's request would amount to 153 billion tons of rice grains, which would need 31 million cargo ships capable of holding 5,000 tons each. The king failed to perceive the nonlinearity in the request and underestimated the accumulation of rice.

Examples of accumulation of nonlinear quantities are pervasive, and the king is not alone in his difficulties of understanding nonlinear accumulation. There is currently growing evidence that a large majority of adults fail to perceive the effects of accumulation of quantities in nonlinear problems in different contexts (Cronin & Gonzalez, 2007; Cronin et al., 2009; Dörner, 1980; Dörner et al., 1997). Research has shown that people have no intuitive feeling for processes that develop nonlinearly, regardless of how common these problems are in the real-world (Cronin et al., 2009). For example, when participants were asked to infer or sketch the shape of accumulation of a nonlinear quantity due to changes in the inflow (a rate that increases the accumulation) and outflow (a rate that decreases the accumulation), more than half responded as if the shape of accumulation was linear (Cronin et al., 2009). According to Cronin et al. (2009), participants could be classified as relying on an intuitive but erroneous heuristic, called “correlation heuristic” (CH), where they incorrectly assume that the accumulation of a quantity

should “look like” or have the same shape as the inflow. According to Cronin et al. (2009), if the inflow is linear, then people relying on CH will infer the accumulation’s shape to be linear as well. Moreover, people’s reliance on CH cannot be attributed to their inability to interpret graphs, contextual knowledge, motivation, and cognitive capacity.

Studying our understanding of nonlinear accumulations is not only important in simple mathematical problems, but also important for global problems with serious socio-economic impact like those concerning the Earth’s climate. For example, well-educated participants with backgrounds in science and mathematics rely on correlational reasoning when judging changes in accumulation of carbon-dioxide (CO<sub>2</sub>) due to changes in emissions and absorptions (Dutt & Gonzalez, 2010; Sterman, 2008; Sterman & Booth Sweeney, 2007). In these studies, participants were given a problem where the CO<sub>2</sub> accumulation was shown to change nonlinearly as a result of both emission (inflow) and absorption (outflow) over time. They were asked to sketch the emission and absorption trajectories that would produce the given trajectory of the CO<sub>2</sub> accumulation. Participants relying on CH, however, misperceived the dynamics of the future CO<sub>2</sub> accumulation. They assumed that if one is to stabilize the accumulation at a level greater than status-quo, then emissions should rapidly increase and stabilize at a higher level as well (Dutt & Gonzalez, 2010; Sterman, 2008; Sterman & Booth Sweeney, 2007). Thus, participants base their inferences solely on the shape of emission and do not consider the shape of both emission and absorption together along with the accumulation’s initial value.

Moreover, as a consequence of relying on CH in cases where emissions increase linearly over time, participants’ correlational (linear) reasoning would grossly underestimate the actual nonlinear increase in the accumulation. This underestimation is a serious problem that results in undervaluing the urgency of the climate change problem and is likely to encourage “wait-and-

see” behavior, according to which people like to defer climate mitigation actions to a time in the future (Dutt & Gonzalez, 2011, 2010; Sterman, 2008). Wait-and-see behavior becomes particularly worrisome for Earth’s climate due to the inherent long delays between the effects of mitigation actions and corresponding changes in atmospheric CO<sub>2</sub> (IPCC, 2007; Sterman, 2008; Sterman & Booth Sweeney, 2007). Even if mitigation actions are started given such delays, atmospheric CO<sub>2</sub> accumulation would continue to rise until emissions equals the absorption rates. Average atmospheric temperature would then peak, and rising sea level from ice melt and thermal expansion would continue (Wigley, 2005; Meehl et al., 2005). Therefore, current wait-and-see policies are likely to cause abrupt, persistent, and costly climatic changes on Earth in the future (Alley et al., 2003; Scheffer et al., 2001).

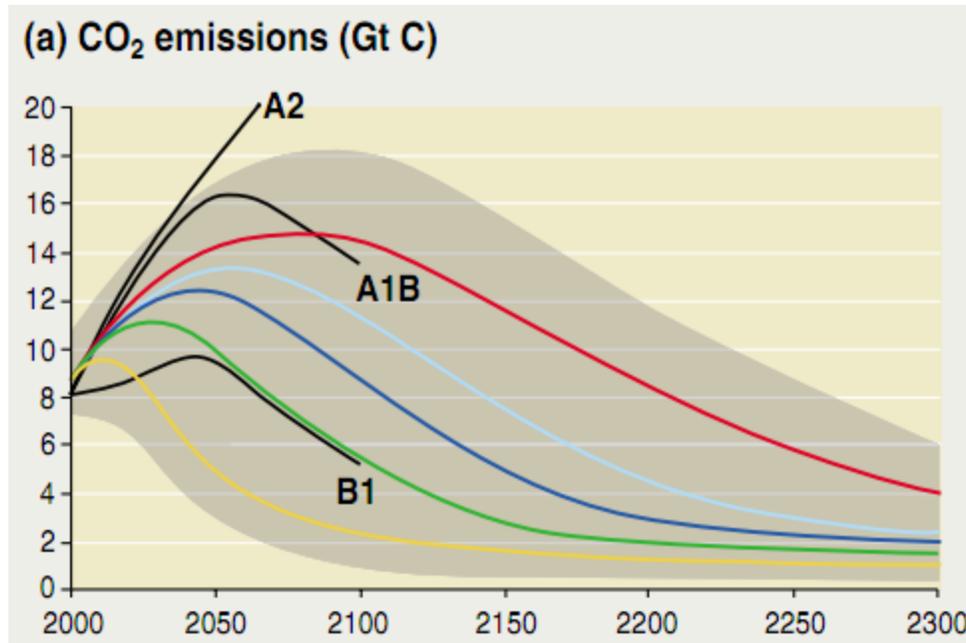
In this paper, we hypothesize that people’s reliance on CH and their consequent underestimation of nonlinear accumulation is influenced by the format in which the information is communicated. Research indicates that when accumulation problems are presented using text or mathematical graphs, responses often rely on CH (Cronin & Gonzalez, 2007; Cronin et al., 2009). This evidence extends to CO<sub>2</sub> accumulations in climate problems (Sterman & Booth Sweeney, 2002, 2007). However, research is critically needed on what presentation formats could reduce people’s reliance on CH (Cronin et al., 2009). Here, we motivate and investigate the use of a physical representation, which presents a problem using a picture as a metaphor.

Experiment 1 evaluates a physical representation against a conventionally used graphical representation in nonlinear problems in two different contexts: a generic non-climate context (i.e., accumulation of marbles in a container) and a specialized climate context (i.e., accumulation of CO<sub>2</sub> in Earth’s atmosphere). Experiment 2 builds upon the results of experiment 1 and investigates the effectiveness of the physical representation against both a text and a

graphic representation in two nonlinear problems that differ in their dynamics: an increasing function where the inflow increases linearly while the outflow is constant, and a decreasing function where the inflow decreases linearly while the outflow is constant. We believe that the use of physical representation will improve people's understanding of nonlinear CO<sub>2</sub> accumulation in the atmosphere, and nonlinear accumulations in other problems and contexts.

### **4.3 Experiment 1: Physical and graphical representations in different contexts**

Research shows that people's reliance on CH in nonlinear problems represented with graphs is robust and increases as the complexity of the problem increases (Cronin & Gonzalez, 2007; Cronin et al., 2009; Dörner, 1980; Dörner et al., 1997). As climate is a complex system and makes extensive use of graphical representations for communicating climate change, it is likely that people would rely on CH. For example, the IPCC (2001a) report has a number of graphical figures that illustrate CO<sub>2</sub> emission scenarios and the corresponding CO<sub>2</sub> accumulation in the atmosphere under each scenario, when projected over time. Figure 4-1 shows an example from the IPCC (2001a) Synthesis Report's Summary for Policymakers. The figure shows different hypothesized CO<sub>2</sub> emission trajectories over a 300 year period. Each of these CO<sub>2</sub> emission trajectories leads to a nonlinear projection for CO<sub>2</sub> accumulation over time (please refer to IPCC, 2001a report for other examples).



**Figure 4-1. A figure taken from the IPCC Synthesis Report’s Summary for Policymakers document. Different emission trajectories (A2, A1B, B1 etc.) are sketched (in Giga tons of Carbon on the Y axis) with respect to time (in years on the X axis). Source: IPCC (2001b; Figure SPM 6a, page 20).**

Similarly, the United States Environment Protection Agency (EPA) explains historic climate change with mathematical graphs detailing nonlinear increases in CO<sub>2</sub> accumulation over time (EPA, 2010), and graphical representations that communicate climate change have also been common in news reports (Schiermeier, 2010).

Prior research has evaluated people’s reliance on CH for climate problems that are presented graphically (Sterman, 2008; Sterman & Booth Sweeney, 2007). In these graphical problems, participants are asked to sketch CO<sub>2</sub> emission and CO<sub>2</sub> absorption that would stabilize CO<sub>2</sub> concentration to an attainable goal by the year 2100. Sterman and Booth Sweeney (2007) report that about 70% of participants (about 60% of whom had backgrounds in science, technology, engineering, and management (STEM), and a majority of the rest in economics) sketched CO<sub>2</sub> emission trajectories that were positively correlated with CO<sub>2</sub> concentration trajectories. Therefore, these participants robustly relied on CH.

We believe that the use of the physical representation to depict CO<sub>2</sub> accumulation, CO<sub>2</sub> emission, absorption, or average atmospheric temperature over time is likely to improve people's understanding of climate change. A physical representation would present a problem using a series of pictures that work as a "metaphor" to explain changes in the quantity of interest. For example, consider a mathematical problem where the length ( $L$ ) of a square's side is doubled and one needs to calculate the new area. A physical representation of the problem will be one where a single square tile of side  $L$  is replaced by four square tiles, each of side  $L$  (i.e., to form a square of side  $2L$ ). There is abundant literature in mathematical education which depicts how and why drawings, pictures, and diagrams, facilitate people's ability to solve mathematical problems when they are presented as metaphors (e.g., Aprea & Ebner, 1999; De Corte et al., 1996; Hall et al., 1997; Larkin & Simon, 1987; Schoenfeld, 1992), and we expect that pictorial metaphors are likely to enable people to reduce underestimation and reliance on correlation heuristic in nonlinear problems. For example, pictorial representations that use an array of icons as a metaphor to represent fractions have been effective in reducing people's tendency to neglect the denominator of a fraction while evaluating a probability or a risk (Garcia-Retamero et al., 2010), and to aid people with low numeracy skills in forming improved judgments about risks in general (Galesic et al., 2009). Also, research has revealed that a picture of a nonlinear problem drawn by students themselves helps them to construct a proper mental representation of the essential elements and relations involved in the problem (Pólya, 1945; Schoenfeld, 1992). Making a drawing or diagram, however, does not guarantee that one will find the solution to a given problem if the representation is incorrect (Van Essen & Hamaker, 1990). According to De Bock et al. (2007), an effective method provides students with a "correct ready-made drawing," or a physical representation of a nonlinear problem as a metaphor that communicates the

dynamics of the problem. Using this idea, Van Dooren et al. (2007) have shown that among school children, the ability to solve nonlinear area problems improves with a physical representation compared to a graphical representation. The performance of the group that was given a physically represented word problem was superior to the group that was given a graphical problem. Thus, we expect that:

**H1:** Estimations of accumulation will be more accurate in a physical representation compared to a graphical representation.

If the physical representation can effectively communicate a problem's dynamics and help participants to answer correctly, we would like to determine how dependent this effect is on a problem's context or cover story. That is because prior research has shown that the general public lacks training in climatology and has little understanding of climate processes (Bostrom et al., 1994; Kasemir et al., 2000; Kempton, 1997; Morgan et al., 2002; Palmgren et al., 2004; Read et al., 1994). Consequently, the climate context with CO<sub>2</sub> accumulation, emission, and absorption processes in Earth's atmosphere, is expected to be unfamiliar compared to other contexts that people encounter in their day-to-day judgments (e.g., accumulation of water in a bathtub with a tap adding water and a drain removing water from the tub, of money in a bank account with income and expenditure, or of marbles in a container with marbles being put in and removed).

Current research is not conclusive regarding the effect of context on problem solving. On one hand, research has shown that people's judgments are often influenced by their familiarity with the context of the problem they solve (Gigerenzer & Hug, 1992). For example, Brunstein, Gonzalez, and Kanter (2010) put nonlinear accumulation problems in the medical context and found that context's familiarity actually hurt participants' performance. Medical students did worse in the medical context compared to in a generic context. Other research, however, reveals

no influence of context on judgment (e.g., Almor & Sloman, 2000; Cronin et al., 2009). For example, Cronin et al. (2009) found no effect of familiarity with the context on participants' reliance on CH. In their design, however, the three contexts used were represented using only graphical representations.

We extend this analysis to a physical representation and its comparison to the graphical representation in both a climate and non-climate context. Given the expected effectiveness of the physical compared to the graphical representation and the lack of consensus regarding the effect of context, we expect that:

**H2:** Estimations of accumulation will be more accurate in a physical representation compared to a graphical representation, regardless of the context used.

### **4.3.1 Participants**

One hundred and thirty-two adults from Pittsburgh, PA were recruited through a website advertisement and participated in this experiment. Forty-four percent were graduate students enrolled in a M.S. or a Ph.D. program, or had completed one of these degrees in the past. The rest were undergraduates either enrolled in an undergraduate program, or had completed a bachelor's degree. Forty-four participants were females. Ages ranged from 18 to 62 years ( $M = 23$  years,  $SD = 6$  years). Sixty-two percent of the participants self-reported having degrees in science, technology, engineering, and management (STEM), and the rest were non-STEM backgrounds. All participants received a flat \$3 compensation for answering an accumulation problem.

### **4.3.2 Experimental Design**

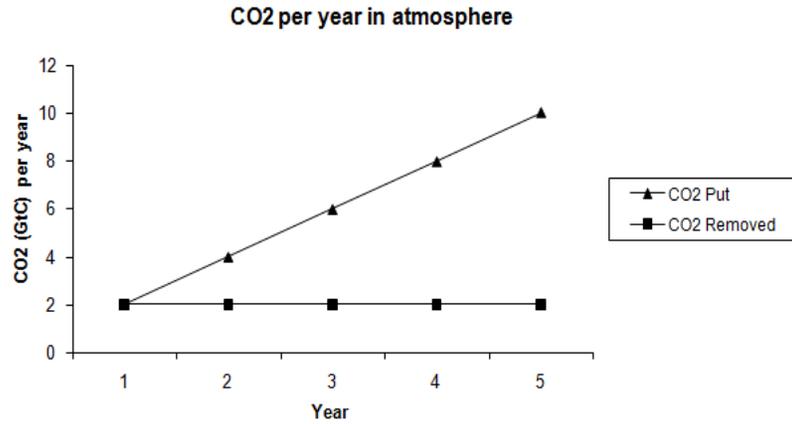
Based upon the two representations and the two contexts within each, participants were randomly assigned to one of four between-subjects treatments: climate context and physical

representation (climate-physical,  $N = 25$ ), climate context and graphical representation (climate-graphical,  $N = 25$ ), marble context and physical representation (marble-physical,  $N = 39$ ), and marble context and graphical representation (marble-graphical,  $N = 42$ ). In each treatment, participants were provided with one accumulation problem that differed in the context and the representation. All four problems were mathematically identical.

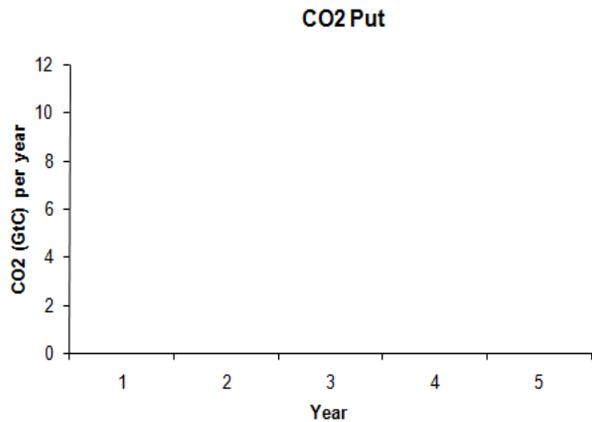
Figure 4-2 shows an example of the graphical representation of the inflow and outflow provided to participants in the climate context. The graphs provided in the marble context were identical. In the climate context, the  $\text{CO}_2$  emission and absorption were the inflow and outflow, respectively. Similarly, in the marble context, the marbles inserted in and removed out of the container were the inflow and outflow. In both contexts, the inflow increased linearly over time while the outflow remained constant over all five time periods. Participants were first asked to sketch the inflow and outflow in a blank graph provided. Asking participants to sketch the given inflow and outflow was done to test their understanding of these flows in the problem. Then, participants were asked to sketch the accumulation in another blank graph provided. As shown in Figure 4-2, participants were given an initial accumulation value (at time = 0), which was depicted as a black dot in the blank graph. The linearly-increasing inflow and constant outflow results in a nonlinear (parabolic) and increasing accumulation. This problem was also used by Cronin et al. (2009) to demonstrate participants' reliance on CH in the graphical representation.

In the physical representation, participants were shown “opaque” containers in three states for each time period: initial state, inflow, and outflow. The units of inflow and outflow are shown as small circles and by using numbers, and the direction of the flow is indicated by arrows (see Figure 4-3 for the corresponding physical representation of the graphical form for the climate context of Figure 4-2).

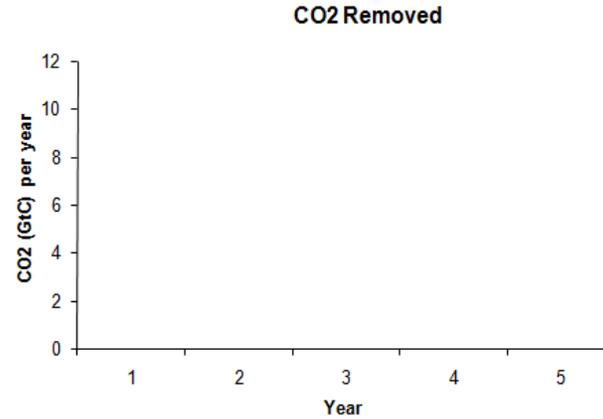
The figure given below shows carbon-dioxide (CO<sub>2</sub>) put and removed from the atmosphere in each of 5 years (GtC = Giga or 10<sup>9</sup> tons of carbon).



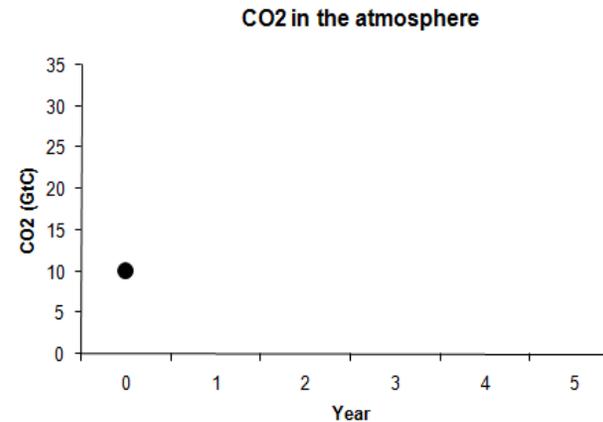
In the space provided below draw the CO<sub>2</sub> put in the atmosphere per year:



In the space provided below draw the CO<sub>2</sub> removed from the atmosphere per year:

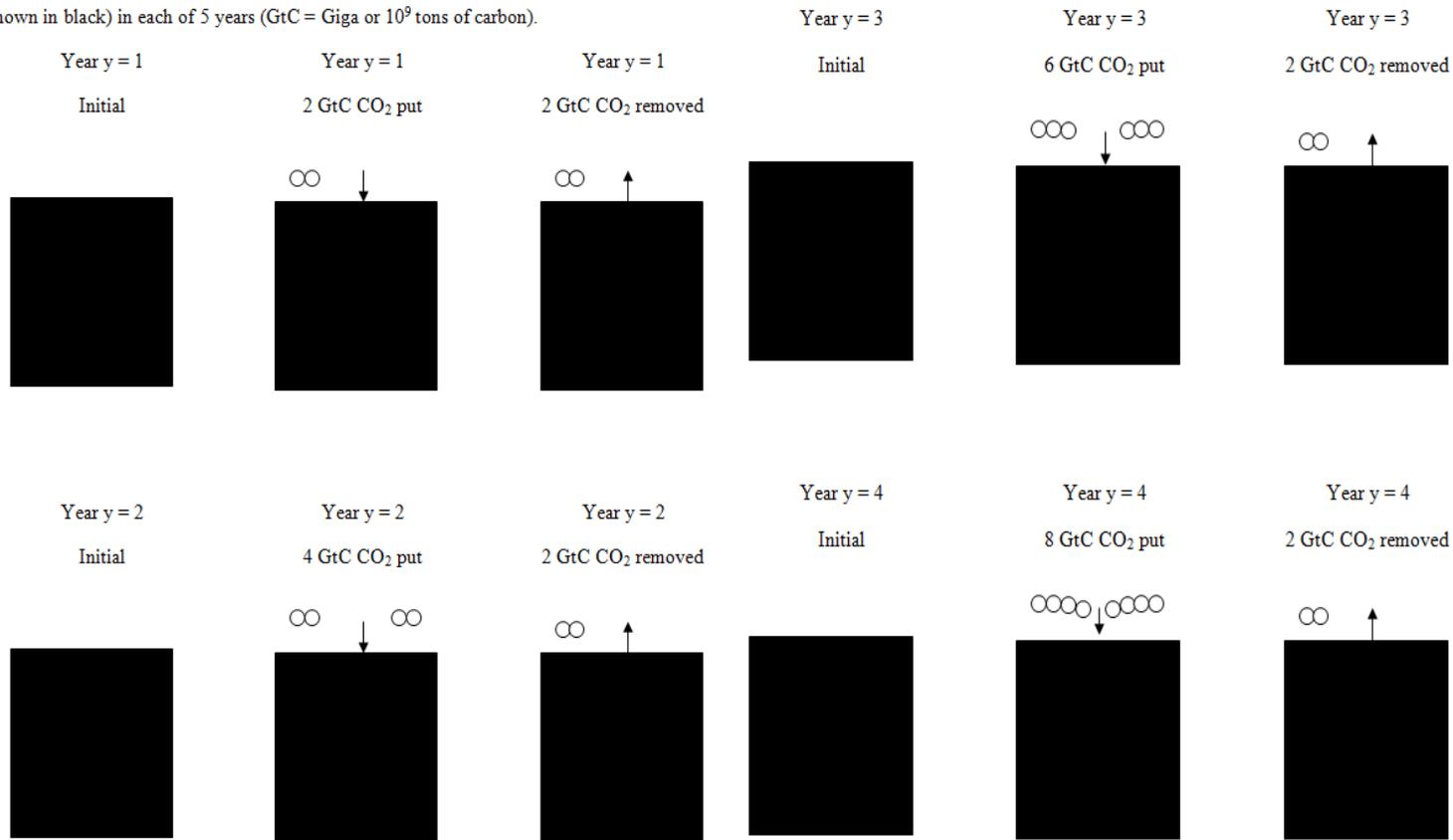


In the space provided below draw the total amount of CO<sub>2</sub> in the atmosphere in each of the 5 years. The initial amount of CO<sub>2</sub> in the atmosphere has been shown as 10 GtC in the first year.

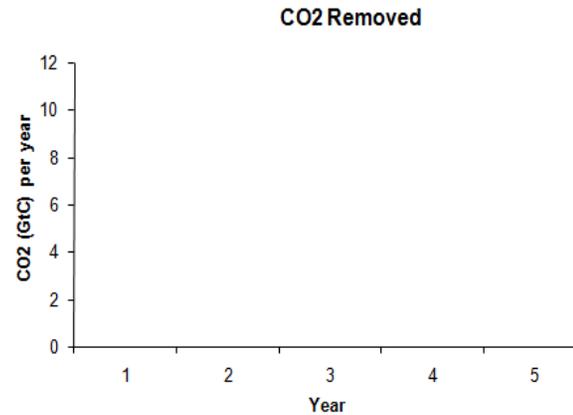
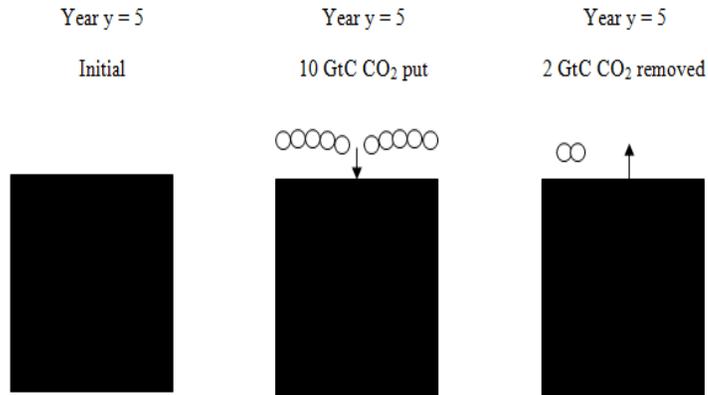


**Figure 4-2. The task presented to the participants in the graphical representation in the climate context in Experiment 1 and 2. Participants were provided with graphs showing changes to the inflow and outflow over time and were asked to sketch the accumulation value over the five time periods due to the changes in the inflow and outflow.**

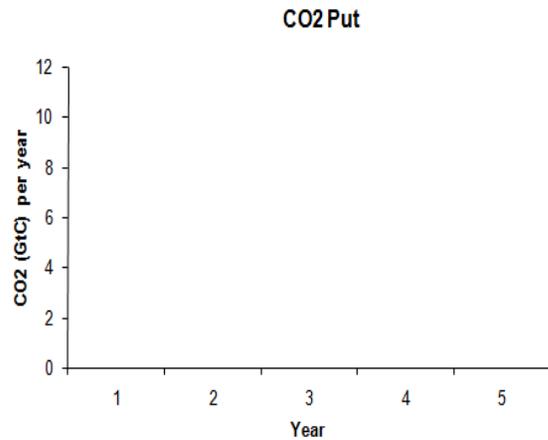
The figures given below shows carbon-dioxide (CO<sub>2</sub>) put and removed from the atmosphere (shown in black) in each of 5 years (GtC = Giga or 10<sup>9</sup> tons of carbon).



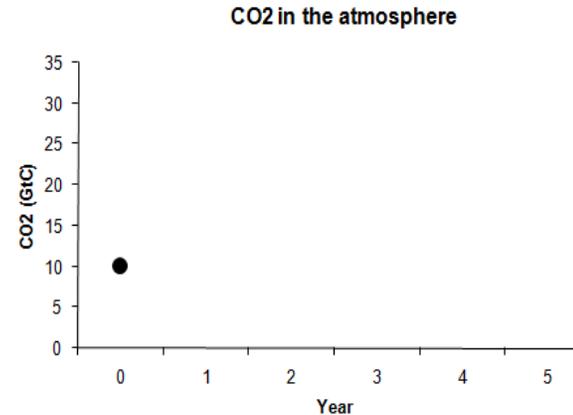
In the space provided below draw the CO<sub>2</sub> removed from the atmosphere per year:



In the space provided below draw the CO<sub>2</sub> put in the atmosphere per year:



In the space provided below draw the total amount of CO<sub>2</sub> in the atmosphere in each of the 5 years. The initial amount of CO<sub>2</sub> in the atmosphere has been shown as 10 GtC in the first year.



**Figure 4-3. The task presented to the participants in the physical representation for the climate context in Experiment 1 and 2. Participants were provided a set of opaque containers that depicted the changed in the inflow and outflow over time. Participants were asked to sketch the accumulation value over the five time periods due to the changes in the inflow and outflow.**

Furthermore, like the graphical representation, participants were asked to sketch the accumulation. Again, the same linearly-increasing inflow and constant outflow as in the graphical representation were used. Participants were asked to read instructions and to sketch the shape of the inflow, outflow, and accumulation over time.

These problems depicted the changes in the inflow and outflow over five time periods (or years) and asked participants to sketch the curve of the inflow, outflow, and the resulting accumulation over that time.

### **4.3.3 Evaluating participants' responses**

The correct accumulation values were the same in all treatments and could be derived by repeatedly using the following equation:

$$S_T = S_{T-1} + I_T - O_T \quad (1)$$

That is the accumulation at time T ( $S_T$ ) is the sum of the accumulation at time T-1 ( $S_{T-1}$ ) and the net inflow (=inflow ( $I_T$ ) – outflow ( $O_T$ ), at time T). For example, given an initial accumulation of 10 units and an inflow and outflow of 2 units each in the first time period, the accumulation at the end of time period 1 will remain at 10 units (= 10 + 2 - 2). Similarly, the accumulation in the second time period (with 4 units inflow and 2 units outflow) will become 12 units. Calculated in the same way, the accumulation in the time periods 3, 4, and 5 will be 16, 22, and 30 units, respectively.

The sketched accumulation values averaged over all participants in each of the five time periods were used as the main source for our analyses. The accumulation values in each of the five time periods were compared to the correct corresponding values. Participants underestimated the correct accumulation if their sketched accumulation values were less than the

correct values. The comparison of the average sketched values with the correct values in each time period allows us to test participants' reliance on CH using one-sample  $t$  tests.

Correlation coefficients were calculated between participants' sketched inflow and outflow values in each of the five time periods and the correct corresponding values that were given to them in the problem. If any of these two correlation coefficients between the sketched and correct inflow and outflow were different from 1.00, then the sketches were marked as incorrect. Moreover, in order to classify participants as relying on CH, we correlated participants' sketched accumulation in each of the five time periods to the correct inflow values. If this score was 1.00, then the sketched accumulation was classified as relying on CH. The coefficient value of 1.00 is a conservative grading scheme because CO<sub>2</sub> emissions are linearly increasing in the problem and any nonlinear increasing sketch of CO<sub>2</sub> accumulation would result in a high positive correlation coefficient. A correlation coefficient value of 1.00 ensures that the relationship between the CO<sub>2</sub> emissions and concentration is none other than perfectly linear and one that follows CH.

#### **4.3.4 Results**

The percent of correct inflow and outflow responses in different treatments were more than 93%. Therefore, participants' understanding of inflows and outflows was similar and highly accurate across different treatments.

To test H1, we compared the participants' average sketched accumulation value in each of the five time periods to the correct corresponding values in the physical and graphical representations (see Table 4-1). There was no difference between the correct accumulation and corresponding average accumulation in the graphical and physical representation in the first three time periods. For the last two time periods, however, the average accumulation in the physical

representation was closer to the correct accumulation, though still less than the correct accumulation, compared to that in the graphical representation. This result is illustrated in Table 4-1 by the weaker  $p$  values, and smaller standard deviations and effect sizes in the physical representation compared to that in the graphical representation for the last two time periods. Estimations of accumulation in the physical representation were more accurate than those in the graphical representation (H1).

**Table 4-1. The correct accumulation in different time periods and their corresponding average accumulation in the graphical and physical representations in Experiment 1.**

Representation	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	10.0 (0.0) <sup>1</sup>	12.0 (0.0)	16.0 (0.0)	22.0 (0.0)	30.0 (0.0)
Graphical (G)	10.4 (2.2)	12.6 (3.4)	15.7 (4.3)	<b>19.6 (5.6)</b>	<b>24.7 (7.7)</b>
Statistics (comparison to Correct)	$t(66)=1.5$ , <i>ns</i> , $r=0.18$ <sup>2</sup>	$t(66)=1.5$ , <i>ns</i> , $r=0.18$	$t(66)=-0.5$ , <i>ns</i> , $r=0.06$	$t(66)=-3.4$ , $p<.001$ , $r=0.39$	$t(66)=-5.7$ , $p<.001$ , $r=0.57$
Physical (P)	10.0 (1.1)	11.9 (1.2)	15.8 (1.5)	<b>21.4 (2.4)</b>	<b>28.8 (4.0)</b>
Statistics (comparison to Correct)	$t(63)=-0.3$ , <i>ns</i> , $r=0.04$	$t(63)=-0.5$ , <i>ns</i> , $r=0.06$	$t(63)=-0.4$ , <i>ns</i> , $r=0.05$	$t(63)=-2.1$ , $p<.05$ , $r=0.26$	$t(63)=-2.4$ , $p<.05$ , $r=0.29$

Note. <sup>1</sup> The values in bracket represent the standard deviation about the mean. <sup>2</sup> The value indicates the effect size.

**Table 4-2. The correct accumulation in different time periods and their corresponding average accumulation in the four treatments in Experiment 1.**

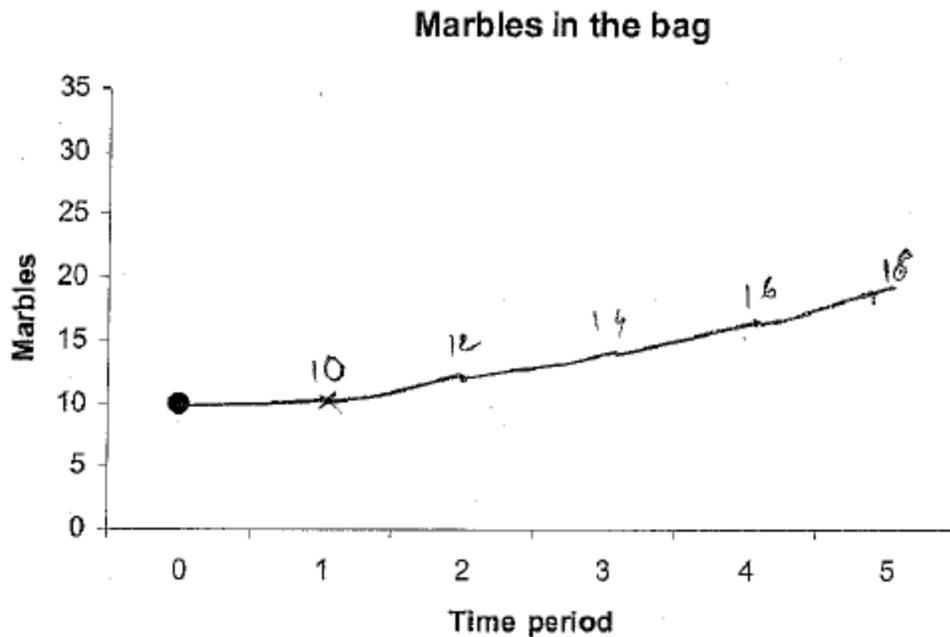
Treatment	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	10.0 (0.0) <sup>1</sup>	12.0 (0.0)	16.0 (0.0)	22.0 (0.0)	30.0 (0.0)
Climate-graphical	10.3 (2.4)	12.3 (2.6)	15.0 (3.1)	<b>18.4 (4.2)</b>	<b>22.6 (6.5)</b>
Statistics (comparison to Correct)	$t(24)=0.6$ , <i>ns</i> , $r=0.12$ <sup>2</sup>	$t(24)=0.6$ , <i>ns</i> , $r=0.12$	$t(24)=-1.5$ , <i>ns</i> , $r=0.29$	$t(24)=-4.3$ , $p<.001$ , $r=0.66$	$t(24)=-5.7$ , $p<.001$ , $r=0.76$
Climate-physical	10.2 (0.8)	12.1 (1.1)	15.9 (1.2)	21.2 (2.3)	28.4 (4.0)
Statistics (comparison to Correct)	$t(24)=1.0$ , <i>ns</i> , $r=0.20$	$t(24)=0.6$ , <i>ns</i> , $r=0.12$	$t(24)=-0.5$ , <i>ns</i> , $r=0.10$	$t(24)=-1.7$ , <i>ns</i> , $r=0.33$	$t(24)=-2.0$ , <i>ns</i> , $r=0.38$
Marble-graphical	10.5 (2.0)	12.8 (3.8)	16.1 (4.9)	20.4 (6.2)	<b>25.9 (8.1)</b>
Statistics (comparison to Correct)	$t(41)=1.6$ , <i>ns</i> , $r=0.24$	$t(41)=1.4$ , <i>ns</i> , $r=0.21$	$t(41)=0.2$ , <i>ns</i> , $r=0.03$	$t(41)=-1.7$ , <i>ns</i> , $r=0.26$	$t(41)=-3.3$ , $p<.01$ , $r=0.46$
Marble-physical	09.8 (1.3)	11.8 (1.3)	15.7 (1.7)	21.4 (2.6)	29.1 (4.0)
Statistics (comparison to Correct)	$t(38)=-0.9$ , <i>ns</i> , $r=0.14$	$t(38)=-1.0$ , <i>ns</i> , $r=0.16$	$t(38)=-0.4$ , <i>ns</i> , $r=0.03$	$t(38)=-1.4$ , <i>ns</i> , $r=0.22$	$t(38)=-1.4$ , <i>ns</i> , $r=0.22$

Note. <sup>1</sup> The values in bracket represent the standard deviation about the mean. <sup>2</sup> The value indicates the effect size.

Table 4-2 presents the correct accumulation in different time periods and the corresponding accumulation in the four treatments to test the effects of context: climate or marble.

There was no difference between the correct accumulation and the corresponding average accumulation in the climate-physical and marble-physical treatments in all five time periods, regardless of the context. The accumulation in the climate-graphical and marble-graphical treatments was less than the correct accumulation in the last two time periods and in the last time period, respectively. Thus, regardless of the context, graphical representations led to underestimations of the accumulation, supporting hypothesis H2.

We analyzed the proportion of responses that relied on CH in the graphical compared to physical representations. Figure 4-4 shows a typical participant's response in the marble-graphical treatment where the response was classified as relying on CH (based upon a 1.0 correlation coefficient between the average accumulation and the inflow given in the treatment). Also, the participant's accumulation in the fifth time period (=18 marbles) underestimated the correct accumulation (=32 marbles) as a result of his relying on CH.



**Figure 4-4.** A typical participant’s response in the marble-graphical treatment which shows participant’s sketched accumulation that was classified as relying on CH. The marbles in the bag (i.e., accumulation) follows a linear trend over time periods (with a constant slope of 2 marbles per time period). The correlation coefficient of the marble accumulation with the inflow (i.e., Marbles put) is 1.0. Also, the accumulation in the fifth time period (=18 marbles) underestimates its correct value (=30 marbles).

Table 4-3 shows that the proportion of responses that were classified as relying on CH was significantly greater in the graphical than the physical representation, regardless of context (climate or marble). That is because of the weaker *p* value and effect size in the physical representation compared to the graphical representation while comparing to a correct response.

**Table 4-3. Proportion of responses classified as relying on the Correlation Heuristic (CH) in different treatments in Experiment 1. Comparison statistics with the correct accumulation’s CH value (= 0%) are also shown.**

Treatment	CH (%)	Statistics (comparison to Correct)
Correct	00	-
Graphical (G)	52	$t(66)=8.5, p<.001, r=0.72$
Climate-graphical	72	$t(24)=7.9, p<.001, r=0.85$
Marble-graphical	40	$t(41)=5.3, p<.001, r=0.64$
Physical (P)	09	$t(63)=2.6, p<.05, r=0.31$
Climate-physical	16	$t(24)=2.1, p<.05, r=0.39$
Marble-physical	05	$t(38)=1.4, ns, r=0.22$

Finally, Table A1 in the Appendix presents results regarding the non-STEM and STEM backgrounds. In the graphical representation, participants' average accumulation underestimated the correct accumulation in the last time period (for non-STEMs) and last two time periods (for STEMs). In the physical representation, there was no difference between the average accumulation and the correct accumulation, regardless of the background. A similar pattern was found for undergraduates, who underestimated the correct accumulation in the last time period and for graduates, who underestimated the correct accumulation in last three time periods (see Table A2 in Appendix). For both backgrounds and levels of education, a smaller proportion of responses were classified as relying on CH in the physical representation than in the graphical representation (for detailed statistics, see Table A3 in the appendix).

#### **4.3.5 Discussion**

In agreement with previous literature in mathematical education (Evangelidou et al., 2004; Leinhardt et al., 1990; Van Deyck, 2001) and on accumulation problems (Cronin et al., 2009), our results show that people underestimate nonlinear accumulations and rely on correlation heuristic in graphical representations. In contrast, a physical representation reduces participants' underestimations as well as their reliance on correlation heuristic; regardless of the context, education background, and levels of education of the participants. Although we can only speculate, it is likely that the physical representation helps people understand the accumulation's basic dynamics: accumulation rises when inflow is greater than the outflow, accumulation falls when the inflow is less than the outflow, and accumulation stabilizes when inflow equals outflow. Due to the use of a metaphor in the physical representation, participants might be able to improve their visualization of the processes that govern the changes in accumulation.

Moreover, this visualization is not completely salient in the graphical representation, and this fact could be a reason for participants' poor performance in the graphical representation.

Furthermore, prior research has also used a text representation to investigate people's reliance on CH in CO<sub>2</sub> accumulation problems (Sterman, 2008; Sterman & Booth Sweeney, 2007). People's reliance on CH has been found to be equally strong in the text representation like in the graphical representation (Cronin et al., 2009). Although this experiment allowed us to test in a physical representation compared to that in a graphical representation, we still do not know whether the physical representation is also as effective compared to the text representation. For this experiment, we used an increasing accumulation problem where the inflow increased linearly, while the outflow was constant. This inflow-outflow behavior caused the accumulation to increase nonlinearly over time. For such an inflow-outflow behavior, reliance on CH made people sketch a linearly increasing accumulation that was similar in shape to the linearly increasing inflow. As a linearly increasing accumulation sketch approximates a nonlinearly increasing accumulation, people's reliance on CH is likely to produce only a small underestimation of the actual accumulation. However, if one considers a decreasing problem where the shape of the inflow decreases over time but it is greater than a constant outflow, then the accumulation will still increase nonlinearly over time. This increase, however, will be in direct opposition to the linearly decreasing inflow. If people rely on CH in this decreasing problem, they would also sketch a linearly decreasing accumulation over time, and their sketch will greatly underestimate the actual nonlinearly increasing accumulation. Moreover, because of the opposing direction of the inflow and accumulation, the decreasing problem is also likely to be a more challenging problem to participants compared to the increasing problem (Dutt, in press; Dutt & Gonzalez, 2007; Gonzalez & Dutt, 2007, 2011; Lebiere et al., in press). Finally,

the decreasing problem also seems to be a realistic case for Earth's climate because policymakers could potentially decide upon interventions in the near future which decrease CO<sub>2</sub> emissions, rather than leave them unregulated and increasing over time. We test the effectiveness of the physical representation against the text representation for the decreasing problem as part of the next experiment.

#### **4.4 Experiment 2: Physical, graphical, and, text representations in increasing and decreasing problems**

As discussed above, people's reliance on CH is also present in nonlinear problems that are presented as text descriptions (Cronin & Gonzalez, 2007; Cronin et al., 2009), which has also been commonly used as part of climate research (Sterman & Booth Sweeney, 2002). In this experiment, we extend our investigation of the robustness of physical representation against both the text and graphical representations in problems with different shapes of inflow: linearly increasing and decreasing. If physical representation is effective in improving people's understanding about the dynamics of emission, absorption, and accumulation in different problems, then we expect:

**H3:** Estimations of accumulation will be more accurate in a physical representation compared to both graphical or text representation, regardless of whether the inflow linearly increases or decreases over time.

In order to test H3, we take two nonlinear problems in the climate context, increasing and decreasing, in three different representations: text (i.e., using a written description), graphical (i.e., using mathematical graphs), and physical (i.e., using pictures).

#### 4.4.1 Participants

One hundred and thirty-two adults from Pittsburgh, PA were recruited through a website advertisement and participated in the experiment. Forty-eight percent were graduate students enrolled in a M.S. or a Ph.D. program, or had previously completed one of these degrees. The rest of the participants were undergraduates either enrolled in an undergraduate program, or had previously completed a bachelor's degree. Forty-seven participants were females. Ages ranged from 18 years to 70 years ( $M = 27$  years,  $SD = 10$  years). Sixty-nine percent of the participants self-reported having degrees in science, technology, engineering, economics, and management (STEM), and the rest had a non-STEM background. Furthermore, participants self-reported to gather news on climate change from the following sources: 3% from books, 52% from Internet, 2% from magazines, 19% from newspapers, 1% from family and friends, 1% from radio, 11% from television, and the rest (11%) reported having no source of news on climate change. Also based upon responses to a question that asked participants about their knowledge on climate change, participants' responses could be summarized as follows: 21% mentioned having no knowledge about climate change, 37% mentioned the causes of climate change (e.g., "climate change is *caused* by..."), 27% mentioned the effects of climate change (e.g., "climate change *leads* to or has the following *effects*..."), and 15% expressed their beliefs about the occurrence/no occurrence of climate change (e.g., "I *believe* climate change will occur..."). All participants received a flat \$3 compensation for answering a nonlinear accumulation problem in the treatment to which they were randomly assigned.

#### 4.4.2 Experimental Design

Participants were randomly assigned to one of six between-subjects treatments: 3 representations (text, graphical, and physical) x 2 (increasing and decreasing) problems. In each

of the six treatments, participants attempted a nonlinear accumulation problem concerning CO<sub>2</sub> accumulation in the atmosphere with different representations and increasing or decreasing inflows (where inflows were greater than a constant outflow): text-increasing (N = 26), text-decreasing (N = 18), graphical-increasing (N = 26), graphical-decreasing (N = 18), physical-increasing (N = 26), and physical-decreasing (N = 18). Just as done in experiment 1, all six problems depicted the changes in the inflow and outflow over five time periods (or years) and asked participants to sketch the curve of the inflow, outflow, and resulting accumulation over the five time periods. The dependent variables used were identical to those used in experiment 1.

Figure 4-5 shows the decreasing problem presented to participants in the text representation. The tabulated inflow (CO<sub>2</sub> emissions) decreased linearly over time from 10 GtC per year to 2 GtC per year, whereas the outflow remained constant (=2 GtC per year). The increasing problem in the text representation was the exactly the same as the decreasing problem, but now the inflow increased linearly over time from 2 GtC per year to 10 GtC per year (outflow was constant at 2 GtC per year). The increasing problem in the graphical and physical representations was identical to that used for the climate context in experiment 1 (except that the initial accumulation was set at 20 GtC instead of 10 GtC so as to keep the initial accumulation equidistant from the two endpoints of the Y axis).<sup>15</sup> The decreasing problem in graphical and physical representation followed the same structure as the increasing problem; however, now the inflow decreased linearly in the problem from 10 GtC per year to 2 GtC per year. As in experiment 1, the correct accumulation in the increasing and decreasing problems could be derived by repeatedly using equation 1.

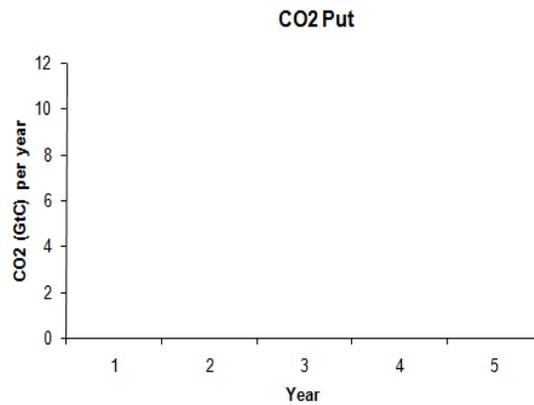
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<sup>15</sup> In experiment 1, we placed the starting accumulation (t=0) below the mid-point of the Y axis. This non-equidistant placement of initial accumulation along with the climate context (where real-world CO<sub>2</sub> accumulations are increasing) could have hinted participants that the accumulation was going to increase over the next five time periods. Furthermore, this could have been a possible reason for their relying on CH in different treatments in this experiment. Therefore, in experiment 2, we correct this methodological issue in our design.

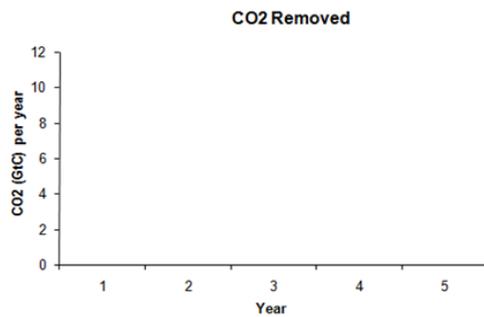
The table given below shows carbon-dioxide (CO<sub>2</sub>) put and removed from the atmosphere in each of 5 years (GtC = Giga or 10<sup>9</sup> tons of carbon).

Year	CO <sub>2</sub> Put (GtC per year)	CO <sub>2</sub> Removed (GtC per year)
1	10	2
2	8	2
3	6	2
4	4	2
5	2	2

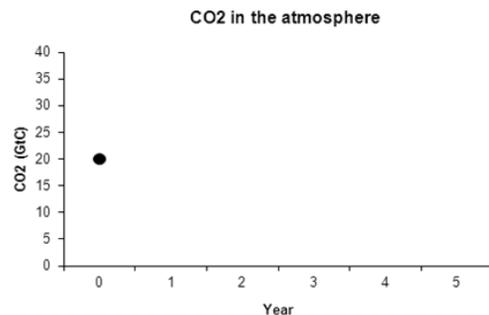
In the space provided below draw the CO<sub>2</sub> put in the atmosphere per year:



In the space provided below draw the CO<sub>2</sub> removed from the atmosphere per year:



In the space provided below draw the total amount of CO<sub>2</sub> in the atmosphere in each of the 5 years. The initial amount of CO<sub>2</sub> in the atmosphere has been shown as 20 GtC.



**Figure 4-5. The decreasing problem presented to participants in the text representation in Experiment 2.**

### 4.4.3 Results

In both the increasing and decreasing problems for different representations, more than 96% of participants correctly sketched the inflow and outflow shapes over time. Thus, participants' understanding about the inflow and outflow in the different representations and in different problems was similar and extremely high.

To test H3, we compared participants' responses in the text and graphical representations to those in the physical representation for both the increasing and decreasing problems. Table 4-4 presents the correct accumulation in different time periods and the corresponding average accumulation given by participants in the graphical, text, and physical representations for each problem. In the increasing problem, the average accumulation in the physical representation was much closer to the correct accumulation compared to that in the graphical or text representations. Upon comparing the graphical and physical representations, we find that these results are in the same direction as reported in experiment 1.

In the decreasing problem, again the accumulation in the physical representation was much closer to the correct accumulation compared to that in the graphical or text representations. The decreasing problem is much more challenging for participants; participants relying on CH would think that the CO<sub>2</sub> accumulation decreases linearly over the five time periods, whereas, relying on CH in the increasing problem would have the accumulation increase linearly over time. Therefore, it is likely to become counter intuitive for participants in the decreasing problem to sketch accumulations that increase over the five time periods. Due to these observations, the underestimation of the correct CO<sub>2</sub> accumulation is found to be greater in the decreasing problem compared to that in the increasing problem. The accumulation reported in the graphical and text representations for the decreasing problem underestimated the correct accumulation much more

than that in the physical representation. In accordance with our expectation about CH reliance, a majority of participants in the text and graphical representation seemed to have sketched their accumulation sloping downwards, similarly to the shape of the linearly decreasing inflow. That is because, as shown in Table 4-4, the accumulation has a negative slope and the accumulation in the fifth time period is less than that in the first time period. However, in the physical representation, the slope of accumulation over time periods is still positive. Taken together, these confirm our expectation in H3: the estimation of accumulation is more accurate in the physical representation compared to that in the graphical and text representations for both increasing and decreasing problems.

**Table 4-4. The correct accumulation in different time periods and their corresponding average accumulation in the graphical, text, and physical representations for the increasing and decreasing problems in Experiment 2.**

Increasing problem					
Representation	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	20.0 (0.0) <sup>1</sup>	22.0 (0.0)	26.0 (0.0)	32.0 (0.0)	40.0 (0.0)
Graphical (G)	18.5 (5.4)	<b>19.9 (5.3)</b>	<b>21.9 (5.6)</b>	<b>24.5 (6.7)</b>	<b>27.6 (9.0)</b>
Statistics (comparison to Correct)	<i>t</i> (25)=-1.4, <i>ns</i> , <i>r</i> =0.27 <sup>2</sup>	<b><i>t</i>(25)=-2.0, <i>p</i>&lt;.05, <i>r</i>=0.37</b>	<b><i>t</i>(25)=-3.7, <i>p</i>&lt;.001, <i>r</i>=0.59</b>	<b><i>t</i>(25)=-5.7, <i>p</i>&lt;.001, <i>r</i>=0.75</b>	<b><i>t</i>(25)=-7.0, <i>p</i>&lt;.001, <i>r</i>=0.81</b>
Text (T)	18.5 (5.4)	20.0 (5.3)	<b>22.1 (5.6)</b>	<b>24.7 (6.7)</b>	<b>27.9 (9.0)</b>
Statistics (comparison to Correct)	<i>t</i> (25)=-1.4, <i>ns</i> , <i>r</i> =0.27	<i>t</i> (25)=-1.9, <i>ns</i> , <i>r</i> =0.36	<b><i>t</i>(25)=-3.6, <i>p</i>&lt;.01, <i>r</i>=0.58</b>	<b><i>t</i>(25)=-5.5, <i>p</i>&lt;.001, <i>r</i>=0.74</b>	<b><i>t</i>(25)=-6.9, <i>p</i>&lt;.001, <i>r</i>=0.81</b>
Physical (P)	20.0 (0.0)	22.0 (0.0)	25.8 (0.7)	31.3 (2.0)	38.6 (3.9)
Statistics (comparison to Correct)	<i>t</i> (25)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (25)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (25)=-1.8, <i>ns</i> , <i>r</i> =0.34	<i>t</i> (25)=-1.8, <i>ns</i> , <i>r</i> =0.34	<i>t</i> (25)=-1.8, <i>ns</i> , <i>r</i> =0.34
Decreasing problem					
Representation	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	28.0 (0.0)	34.0 (0.0)	38.0 (0.0)	40.0 (0.0)	40.0 (0.0)
Graphical (G)	<b>19.0 (8.9)</b>	<b>20.1 (12.4)</b>	<b>20.4 (15.2)</b>	<b>20.0 (17.1)</b>	<b>18.8 (18.1)</b>
Statistics (comparison to Correct)	<b><i>t</i>(17)=-4.3, <i>p</i>&lt;.001, <i>r</i>=0.72</b>	<b><i>t</i>(17)=-4.7, <i>p</i>&lt;.001, <i>r</i>=0.75</b>	<b><i>t</i>(17)=-4.9, <i>p</i>&lt;.001, <i>r</i>=0.77</b>	<b><i>t</i>(17)=-5.0, <i>p</i>&lt;.001, <i>r</i>=0.77</b>	<b><i>t</i>(17)=-5.0, <i>p</i>&lt;.001, <i>r</i>=0.77</b>
Text (T)	<b>18.0 (9.2)</b>	<b>19.4 (13.2)</b>	<b>19.9 (16.0)</b>	<b>19.3 (17.8)</b>	<b>17.8 (18.7)</b>
Statistics (comparison to Correct)	<b><i>t</i>(17)=-4.6, <i>p</i>&lt;.001, <i>r</i>=0.74</b>	<b><i>t</i>(17)=-4.7, <i>p</i>&lt;.001, <i>r</i>=0.75</b>	<b><i>t</i>(17)=-4.8, <i>p</i>&lt;.001, <i>r</i>=0.76</b>	<b><i>t</i>(17)=-4.9, <i>p</i>&lt;.001, <i>r</i>=0.77</b>	<b><i>t</i>(17)=-5.0, <i>p</i>&lt;.001, <i>r</i>=0.77</b>
Physical (P)	<b>22.0 (8.2)</b>	<b>25.1 (11.9)</b>	<b>27.0 (14.8)</b>	<b>27.7 (16.7)</b>	<b>27.1 (17.6)</b>
Statistics (comparison to Correct)	<b><i>t</i>(17)=-3.1, <i>p</i>&lt;.01,</b>	<b><i>t</i>(17)=-3.2, <i>p</i>&lt;.01,</b>	<b><i>t</i>(17)=-3.2, <i>p</i>&lt;.01,</b>	<b><i>t</i>(17)=-3.1, <i>p</i>&lt;.01,</b>	<b><i>t</i>(17)=-3.1, <i>p</i>&lt;.01,</b>

$r=0.60$        $r=0.61$        $r=0.61$        $r=0.60$        $r=0.60$

*Note.* <sup>1</sup> The values in bracket represent the standard deviation about the mean. <sup>2</sup> The value indicates the effect size.

Furthermore, greater underestimation in text and graphical representations compared to the physical representation is likely due to participants' reliance on CH. The procedure followed to classify a participant's response as relying on CH was identical to in experiment 1. Table 4-5 shows the proportion of responses classified as relying on CH in different treatments. If participants responded correctly, then their sketched accumulations will be nonlinear in shape and would not be classified as relying on CH (the correct accumulation shape therefore has 0% CH). In both increasing and decreasing problems, the proportion of responses classified as relying on CH was less for the physical representation compared to the graphical and text representations.

**Table 4-5. Proportion of responses classified as relying on the Correlation Heuristic (CH) in different representations and problems in Experiment 2. Comparison statistics with the correct accumulation's CH value (= 0%) are also shown.**

Increasing problem		
Representation and Education	CH (%)	Statistics (comparison to Correct)
Correct	00	-
Graphical (G)	73	$t(25)=8.2, p<.001, r=0.85^1$
Text (T)	69	$t(25)=7.5, p<.001, r=0.83$
Physical (P)	12	$t(25)=1.8, ns, r=0.34$
Decreasing problem		
Treatment	CH (%)	Statistics (comparison to Correct)
Correct	00	-
Graphical (G)	61	$t(17)=5.2, p<.001, r=0.78$
Text (T)	56	$t(17)=4.6, p<.001, r=0.74$
Physical (P)	33	$t(17)=2.9, p<.01, r=0.58$

*Note.* <sup>1</sup> The value indicates the effect size.

Finally, we also tested the effectiveness of the physical representation compared to the graphical and text representations for each problem among different education backgrounds and education levels. For STEMs and non-STEMs in both problems, estimates of the accumulation

were much closer to the correct in the physical representation compared to the graphical and text representations (see Table B1 in the appendix). Again in both problems, both the undergraduates' and graduates' accumulation were generally more accurate in the physical representation than that in the graphical and text representations (see Table B2 in the appendix). Similarly, the proportion of responses relying on CH among STEMs and non-STEMs in the physical representation was much less compared to that among STEMs and non-STEMs in the graphical and text representations, respectively (see Table B3 in the appendix). Also, a similar relationship was observed among graduate and undergraduate levels of education (see Table B3 in the appendix).

#### **4.4.4 Discussion**

Our results indicate that the physical representation is more effective compared to both the text and graphical representations across different problem types, and is effective in reducing participants' reliance on CH. Even though participants' understanding about inflow and outflow was no different in different treatments, the physical representation decreased participants' CH reliance. The decrease in CH reliance in the physical representation was despite the fact that the relationship between the accumulation and inflow is counter-intuitive in the decreasing problem: the emissions decrease linearly, although the actual CO<sub>2</sub> accumulation continues to increase nonlinearly over time. This is observed in both the graphical and text representations for our results; the average sketched accumulation over the five time periods had a negative slope. In the physical representation, however, the slope of the average sketched accumulation over the five time periods was positive. Taken together, these findings reinforce the effectiveness of the physical representation in different problems and compared to different representations. The

physical representation's effectiveness makes it suitable for use in different kinds of dynamic problems, where the resulting shape of the inflow might be different over time.

## **4.5 General Discussion**

People underestimate the correct value of nonlinear accumulation given their reliance on the correlation heuristic for different contexts and problems. The use of a physical representation, however, can help reduce people's underestimation and reliance on the correlation heuristic in nonlinear accumulation problems, regardless of the problem's dynamics or context, and participants' educational backgrounds and education levels.

Considering its effectiveness in our results, the use of a physical representation may motivate participants to get involved in the problem they're solving, and may help them construct a correct representation of the problem. Research that has investigated physical representation in the past has also concluded similarly for the representation's effectiveness (Cooper & Harris, 2002, 2003; De Lange, 1987; Freudenthal, 1983; Palm, 2002). Given its effectiveness in our results and the documented benefits in mathematical education and judgment and decision making literature (Aprea & Ebner, 1999; De Corte et al., 1996; Galesic et al., 2009; Garcia-Retamero & Galesic, 2010; Garcia-Retamero et al., 2010), physical representations will also be effective in reducing correlation heuristic reliance in a wider range of nonlinear problems and contexts.

Generally, one could imagine many different physical representations in nonlinear problems that depend upon what needs to be communicated to a decision maker in these problems. For example, in order to communicate fractions, probability, or risk, an icon array has been found to be very effective (Galesic et al., 2009; Garcia-Retamero & Galesic, 2010; Garcia-Retamero et al., 2010). The physical representation we used here provided a picture snapshot of

the inflows and outflows at any instance of time to a decision maker. A possible limitation of our representation is that it might be impractical for problems with a larger time scale. One could depict the changes in flows only for the first few and last few time periods in problems with a larger time scale, and may still reap the benefits of using a physical representation. By doing so, one is likely to be able to communicate the correct understanding of accumulation in a problem.

In this paper, we have shown that the physical representation is effective in both climate and non-climate contexts. Therefore, the use of physical representation would be of immense potential to improving public understanding in these contexts. As the current wait-and-see policies for Earth's climate are likely to cause catastrophic changes in the near future (Alley et al., 2003; Scheffer et al., 2001), however, our findings are particularly relevant to research on wait-and-see behavior for climate change. With wait-and-see behavior, people prefer to delay policy actions that mitigate climate change to a future time. The changes in atmospheric CO<sub>2</sub> accumulation (which is one of the main contributors for climate change) has been increasing nonlinearly for many years since the Industrial Revolution (IPCC, 2007). Furthermore, the accumulation's nonlinear increase is predicted to intensify over the next 50-60 years (IPCC, 2007), with adverse consequences like temperature change, melting of polar icecaps, and rising sea levels (Alley et al., 2003; Scheffer et al., 2001). As seen in our findings, people tend to underestimate a nonlinear change in the CO<sub>2</sub> accumulation, when inferring from text and graphical representations. Because text and graphical representations are commonly used to communicate climate change (IPCC, 2001a; EPA, 2010; Schiermeier, 2010), people are likely to underestimate the CO<sub>2</sub> accumulation's nonlinear change and inaccurately infer much less CO<sub>2</sub> in the atmosphere compared to that predicted by climate scientists. Underestimating the CO<sub>2</sub> accumulation is likely to undermine the importance of the climate problem, and this could result

in people's wait-and-see behavior. A physical representation could be used to represent the CO<sub>2</sub> accumulation information and communicate the dynamics of Earth's climate. Using the physical representation over other forms like text or graphs, we might be able to improve our estimation on atmospheric CO<sub>2</sub> and its associated global warming, and may ultimately reduce people's wait-and-see behavior.

Let us return to the fable about the inventor of chess and the king. By now, it becomes easier to explain why the king thought that the inventor's request was *modest*; He was unable to foresee how the accumulation of rice was nonlinear. He underestimated the rice accumulation much like our participants did on nonlinear accumulation problems. But the king realized the cleverness of the inventor's request halfway through fulfilling it. The actual "physical exercise" of putting the rice grains on the chess board's squares was an example of a physical representation. As shown by the current research, the use of physical representation enables people to overcome underestimation of accumulation in nonlinear problems.

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## **4.7 Next Chapters' Highlights**

As it might be difficult to change people's correlational or linear thinking processes in the real world, the next two chapters (5 and 6) discuss how one could instead rely on these processes to enable people to make decisions that are better for Earth's climate. Furthermore, chapter 5 extends this analysis to people from both policy and general backgrounds.

## **Chapter 5: Using Cognitive Factors to Improve Environmental Decisions – Application to Earth’s Climate**

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### **Responding linearly in nonlinear problems: Application to Earth’s climate**

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## 5.1 Abstract

Past research has shown that a majority of people exhibit robust linear thinking for nonlinear changes in their decision environment. We argue that linear thinking could be particularly problematic in the case of interpreting carbon-dioxide's (CO<sub>2</sub>) lifetime in the earth's atmosphere. Participants from policy and non-policy backgrounds were asked to rank five ranges of CO<sub>2</sub> percentages to be removed from the atmosphere according to their impact on CO<sub>2</sub>'s lifetime in two separate conditions: Aid and no-Aid. In the Aid condition, participants were provided with a descriptive decision aid through instructions that might enable them to answer the problem correct, while this aid was absent in the no-Aid condition. Two problems were presented to each participant in random order: Linear, where a ranking based upon linear thinking yielded a correct rank order; and Nonlinear, where a ranking based upon linear thinking yielded an incorrect rank order. Results reveal that a majority of participants from both backgrounds responded linearly on both problems and although the decision aid had no effect on participants' correct responses, it enabled policy backgrounds to move away from responding according to linear thinking. We discuss implications of these findings on policymaking about climate change.

*Keywords:* carbon-dioxide gas's lifetime; linear thinking; climate change; aid; nonlinear problems.

## 5.2 Introduction

According to Galileo Galilei (Galilei, 1638), Aristotle believed that the speed with which an object falls is *linearly* related to its weight. Thus, comparing dropping a ball weighting 100 kg and another weighting 1 kg from the same height, the heavier ball will fall 100 times faster. Responding *linearly* as Aristotle did refers to a function,  $f(x) = a \cdot x$ , where  $f(x)$  is a person's decision response,  $x$  is a change in the decision environment, and  $a$  is different from zero<sup>16</sup> (Freudenthal, 1983). Many centuries later, Galileo proved Aristotle's reasoning as wrong, but it is unclear whether our tendency to respond linearly to nonlinear problems has been solved.

Currently, there is burgeoning amount of evidence that a majority of people think linearly when encountering nonlinear problems in their decision environment (Cronin, Gonzalez, & Sterman, 2009; Dörner, Kimber, & Kimber, 1997; Dutt & Gonzalez, 2009a, 2011; Larrick & Soll, 2008; Van Dooren, De Bock, Janssens, & Verschaffel, 2007). For example, more than 90% of students at the end of elementary school responded "170 seconds" to the question: "John's best time to run 100 meters is 17 seconds. How long will it take him to run 1 kilometer?" (Greer, 1993). Similarly, many people wrongly believe that "3,500 calories consumed is a pound," or for every 3,500 "extra" calories consumed, you will gain one pound (Chow, 2010).<sup>17</sup> In fact, the tendency to respond linearly has been shown to pervasively affect human judgment in global problems involving serious socio-economic consequences such as those concerning the earth's climate (Dutt & Gonzalez, 2009a, 2011; Sterman, 2008; Sterman & Booth Sweeney, 2007). For example, Dutt and Gonzalez (2009b) have shown that when university students were asked to estimate the shape of a carbon-dioxide (CO<sub>2</sub>) accumulation and given linear changes in CO<sub>2</sub>

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<sup>16</sup> If  $a = 0$ , then the relationship is constant ( $= 0$ ) rather than linear. For a constant relationship, a person's decision response is independent of environmental changes.

<sup>17</sup> The actual relationship between the changes in body weight over time is nonlinear, and is a function of a person's food intake and the difference of one's current body weight from a reference body weight (Chow, 2010).

emissions and absorptions over time, a majority drew a linear shape for the accumulation that was similar to the linear shape of CO<sub>2</sub> emissions over time. Similarly, Sterman and Booth Sweeney (2007) and Sterman (2008) have shown that people often misperceive the dynamics of CO<sub>2</sub> accumulation; assuming that if one is to increase the accumulation, then CO<sub>2</sub> emissions should increase as well in a shape similar to the accumulation. This tendency to respond linearly is also related to people's level of education in science and technology (STEM) (Dutt & Gonzalez, 2009b), where people with backgrounds in STEM seem to respond less linearly compared to non-STEM backgrounds.

A prediction that the shape of an accumulation “looks like” the shape of the inflow is an example of robust linear thinking called the *correlation heuristic* (CH) (Cronin et al., 2009). According to Cronin et al. (2009), the proportion of participants relying on the CH increased as the nonlinear relationship between the inflow, outflow, and accumulation became more complex. In the case of the earth's climate, people may underestimate the extent of the nonlinear increase in CO<sub>2</sub> accumulation (Dutt & Gonzalez, 2010). That is because the shape of CO<sub>2</sub> emissions (inflow) has been increasing about linearly over time (IPCC, 2007), and people might think that the accumulation will also increase linearly. In practice, an assumption of linear increase will underestimate the actual increase. Furthermore, such underestimations could undermine the urgency of the climate problem and encourage deferment of human actions, leading to *wait-and-see* behavior (Dutt & Gonzalez, 2009a, 2011; Sterman, 2008; Sterman & Booth Sweeney, 2007).

It has been argued that overreliance on linear thinking is partly due to its simplicity (Fischbein, 1999; Freudenthal, 1983; Lesh, Post, & Behr, 1988; Rouche, 1989). For example, Rouche (1989) argued that “it is the idea of proportionality that comes immediately in the mind, because undoubtedly there are no functions that are more simple than the linear ones” (pg. 17). Similarly, Freudenthal (1983) commented that “linearity is such a suggestive property of

relations that one readily yields to the seduction to deal with each numerical relation as though it were linear” (pg. 267).

Furthermore, literature on heuristics and biases show that simple linear models lead to approximate correct responses that are more accurate than even expert judgments (Dawes, 1979; Goldberg, 1970). For example, Dawes (1979) gives the example of predicting something as abstract as “professional self-actualization.” Given students’ graduate record examination, grade point average, and letters of recommendation, one could create a simple linear model to predict the students’ professional self-actualization (self-actualization was measured for a set of students based upon their achievement post-graduation from the university). When Dawes and Corrigan (1974) applied different linear models to five different datasets to predict the criterion, an equal weighting linear model (the simplest assumption of linearity) outperformed all other competing models. Thus, simple linear assumptions can be accurate in many situations, and people depend upon it because it yields an accurate answer in many situations.

Concrete interventions can help reduce linear thinking in both simple and complex nonlinear problems (Cronin et al., 2009; Larrick & Soll, 2008; Garcia-Retamero, Galesic, Gigerenzer, 2010). For example, a physical representation of a nonlinear problem that uses pictures as “metaphors” helped participants reduce their reliance on linear thinking and increased their accuracy (Dutt & Gonzalez, 2010). Although these interventions seem to be effective in reducing reliance on linear thinking, they require people to *change* their cognitive thought processes in nonlinear problems, where such a change might at times become very difficult or even impossible to attain (Klayman & Brown, 1993).

This paper demonstrates robust reliance on linear thinking in a nonlinear environmental problem. It tests concrete interventions to help people respond correctly *without changing* their

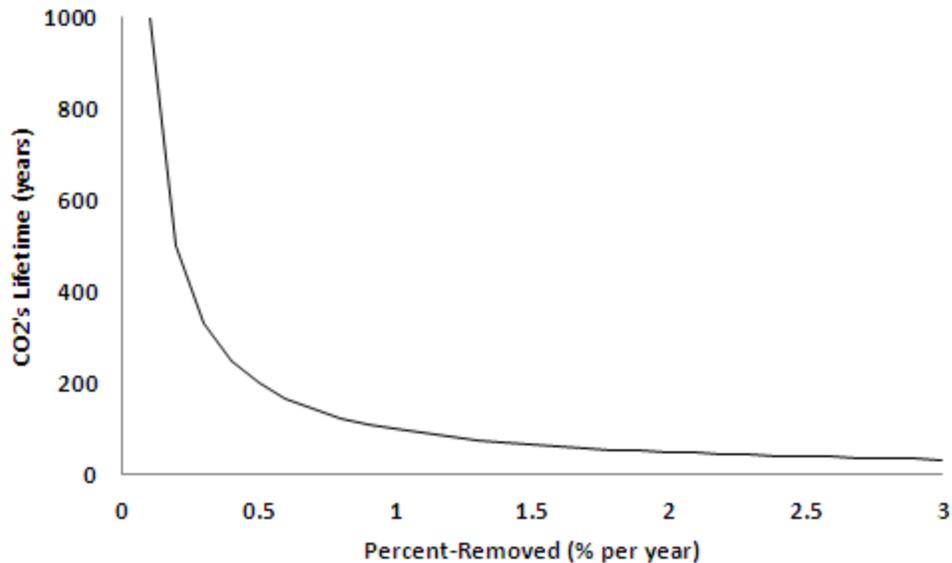
tendency to think linearly.<sup>18</sup> One intervention is to present a nonlinear problem in a way where linear thinking results in a correct response. Some research has shown that a change in the information context can enable people to make correct responses without influencing their natural thought process (Klayman & Brown, 1993; Payne, Bettman, & Schkade, 1999). Another intervention is to encourage participants through instruction to think nonlinearly; an intervention that tries to change a participant's thought process. Recent research has shown that a *nudge* given in the form of written instructions might enable improved decisions (Thaler & Sunstein, 2008). Furthermore, we evaluate whether participants' policy backgrounds influence their reliance on linear thinking in these problems. Because decisions about environmental problems are made by policymakers, it is important to determine if the participant's background in politics, business, economics, and law influence their thinking compared to non-policy backgrounds. According to Nordhaus (1994), the policy background is highly representative of the backgrounds possessed by policymakers who decide on environmental issues facing the world.

### 5.3 The Nonlinear CO<sub>2</sub> Lifetime Problem

The lifetime of CO<sub>2</sub> in the atmosphere (in units of years) is the time it takes to remove a certain mass of CO<sub>2</sub> from the atmosphere. CO<sub>2</sub> lifetime is naturally affected by the yearly percentage of CO<sub>2</sub> removed ("percent-removed" hereafter) by natural processes like absorptions by oceans and photosynthesis in plants (IPCC, 2007). A large percent-removed is desirable because larger quantities of accumulated CO<sub>2</sub> leads to climate change and increasing average temperature (IPCC, 2007). Figure 5-1 exemplifies CO<sub>2</sub>'s lifetime in the atmosphere as a nonlinear function of its percent-removed: the lifetime of CO<sub>2</sub> in the atmosphere (units: years) = 100 / percent-removed (units: percent per year).

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<sup>18</sup> We discuss other problems in the discussion section where linear thinking could result in a correct response based upon the problem's presentation.



**Figure 5-1. The nonlinear relationship between CO<sub>2</sub>'s lifetime and percent-removed in the CO<sub>2</sub> lifetime problem.**

As shown in Figure 5-1, a decrease in the percent-removed corresponds to a nonlinear increase in CO<sub>2</sub> lifetime. In addition, the percent-removed is expected to decrease in future years, as oceans and plants are expected to have a reduced ability to absorb CO<sub>2</sub>, resulting in a large increase in atmospheric CO<sub>2</sub> lifetime (Cramer et al. 2001; Joos et al. 2001; Matear & Hirst, 1999; Sarmiento & Quéré, 1996). Given the nonlinear relationship between the percent-removed and CO<sub>2</sub> lifetime, the equal range of reduction in percent-removed may result in a very large or very small increase in CO<sub>2</sub> lifetime, depending on where the range falls on the non-linear curve (see Figure 5-1). For example, a percent-removed reduction from 0.3 to 0.1 (i.e., 0.2 range) per year results in a 667 years increase for CO<sub>2</sub> lifetime. A reduction from 0.8 to 0.6 (i.e., a similar 0.2 range) per year, however, results in only a 42 years lifetime increase.

Consistent with the substantial evidence of human linear thinking in nonlinear problems, we expect that participants will think linearly when asked to judge the effect of a decrease in CO<sub>2</sub>'s percent-removed on an increase in CO<sub>2</sub> lifetime: they would believe that the *largest* reduction in percent-removed would result in the *largest* increase in lifetime. Thus, we expect:

**H1a:** A larger proportion of linear responses than nonlinear responses.

Furthermore, we expect that by presenting a problem where a linear response leads to a correct response, we will enable participants to make correct responses even when relying on linear thinking (Klayman & Brown, 1993; Payne et al., 1999). We accomplish this by changing the presentation of information in the decision environment. This manipulation is strictly in the decision environment, not a treatment to change participants' thought processes. Such an approach has also been suggested in other judgment research (Larrick, 2004; Klayman & Brown, 1993; Payne et al., 1999). In other cases, however, linear thinking would lead to incorrect responses. Thus, we hypothesize that:

**H1b:** The proportion of correct responses will be greater when the correct response in the problem is aligned with linear thinking compared to when it is not.

Furthermore, another way to improve participants' decision making is to provide them with a descriptive aid through instruction (Thaler & Sunstein, 2008). The aid could be in the form of a statement that suggests to convert a CO<sub>2</sub>'s percent-removed value to a CO<sub>2</sub>'s lifetime value (where CO<sub>2</sub>'s lifetime = 100 / percent-removed as seen in Figure 5-1) and make it simpler for them to calculate the linear increase in CO<sub>2</sub>'s lifetime. Using CO<sub>2</sub>'s lifetime information will help a person reduce the nonlinear problem to a linear one, making it easy to answer the problem correctly. It is to be noted that unlike the above manipulation that changed a person's decision environment, this aid manipulation is aimed at changing a person's linear thought process. Thus, we hypothesize that:

**H2:** The proportion of correct responses will be greater for those who are given an aid than those who are not given an aid.

Finally, according to Dutt and Gonzalez, (2009b), a greater proportion of STEMs provided correct responses in nonlinear problems compared to non-STEMs. A possible reason for this finding is that STEMs possess greater expertise in mathematical problem solving (Chi, 2006). For example, Chase and Simon (1973) found that expertise and skill in chess enabled participants to recognize significant patterns and remember them easily. Similarly, experience in mathematical problem solving might enable STEMs to respond appropriately in nonlinear problems. Currently, there is dearth of research that directly investigates people with policy backgrounds' linear responses in nonlinear problems. If policy backgrounds possess some expertise in policymaking, then they should respond more accurately in the CO<sub>2</sub> lifetime problem. Thus, we expect:

**H3:** A larger proportion of correct responses by those with policy backgrounds compared to those with non-policy backgrounds.

## **5.4 Methods**

### **5.4.1 Participants**

Sixty-seven participants participated in this experiment and were recruited using an online advertisement. Twenty-three participants were from a policy background, and possessed or were pursuing degrees in political science (N=3), business (N=2), economics (N=5), policy (N=9), and law (N=4). The rest of the participants (N=44) had non-policy backgrounds. Thirty-three participants were females. Ages ranged from 18 to 52 years (Mean= 25, SD= 6). Forty-nine percent of participants were either enrolled in a graduate degree or had completed a graduate degree in the past. Forty-four percent of participants with a policy background and fifty-two percent of participants with a non-policy background were either enrolled in a graduate degree or had completed a graduate degree in the past, respectively. All sixty-seven participants reported

knowing some information about climate change through television, radio, newspaper, magazine, movie, or a talk with family or friends. Ten and thirteen participants with policy backgrounds were randomly assigned to the no-Aid and Aid conditions, respectively. Twenty-five and nineteen participants with non-policy backgrounds were randomly assigned to the no-Aid and Aid conditions, respectively. All participants received a flat compensation of \$5 in the experiment, which lasted for about 10 minutes.

#### **5.4.2 Materials and Procedure**

Each participant was presented with two problems in random order. One of the problems is aligned correctly with linear thinking (Linear) while the other problem is not (Nonlinear). "Aligning correctly" with linear thinking meant that the problem was presented such that a linear response would yield a correct response, while "aligning incorrectly" meant that the problem was presented such that a linear response would yield an incorrect response. Each problem consisted of five ranges of decreasing values of CO<sub>2</sub> percent-removed per year, with a From (status-quo and higher) and a To (future and lower) value. Participants were asked to rank the percent-removed ranges from the one that would cause the largest increase in CO<sub>2</sub> lifetime (rank 1) to the smallest increase (rank 5) (see Figure 5-2 for full instructions). Participants were also requested to clearly show their math in the space provided.

Participants were randomly assigned to one of two conditions, Aid or no-Aid. In the Aid condition, participants were given the following statement as part of the instructions: "For calculations, the climate scientist has suggested that you translate the yearly percentage of CO<sub>2</sub> removed values (in percentage of CO<sub>2</sub> per year) into the lifetime that CO<sub>2</sub> stays in the atmosphere (in years)." This sentence was omitted from the instructions for participants assigned to the no-Aid condition.

### Aid Condition, Linear Problem

The table below gives you the pairs of "From" and "To" yearly percentage of CO<sub>2</sub> removed values. Please rank order these values in terms of their detriment to Earth's climate from 1 to 5:

- Use 1 for the **most** detrimental pair: the pair that would cause the most increase of lifetime of CO<sub>2</sub> in the atmosphere.
- Use 5 for the **least** detrimental pair: the pair that would cause the least increase of lifetime of CO<sub>2</sub> in the atmosphere.

You are allowed to use a computer screen calculator, in case you need one. But you also need to clearly show your work (i.e. your mathematical formulation) in the space provided below the table. For calculations, the climate scientist has suggested that you translate the yearly percentage of CO<sub>2</sub> removed values (in percentage of CO<sub>2</sub> per year) into the lifetime that CO<sub>2</sub> stays in the atmosphere (in years).

Pairs		Rank (1 to 5)
From	To	
1.9% per year now	0.5% per year in future	
2.1% per year now	0.1% per year in future	
2.0% per year now	0.3% per year in future	
1.7% per year now	1.1% per year in future	
1.6% per year now	0.9% per year in future	

Please clearly show your work i.e. the math you did for getting the ranks in the table above (you are allowed to use a computer screen calculator for any calculations):

### Aid Condition, Nonlinear Problem

The table below gives you the pairs of "From" and "To" yearly percentage of CO<sub>2</sub> removed values. Please rank order these values in terms of their detriment to Earth's climate from 1 to 5:

- Use 1 for the **most** detrimental pair: the pair that would cause the most increase of lifetime of CO<sub>2</sub> in the atmosphere.
- Use 5 for the **least** detrimental pair: the pair that would cause the least increase of lifetime of CO<sub>2</sub> in the atmosphere.

You are allowed to use a computer screen calculator, in case you need one. But you also need to clearly show your work (i.e. your mathematical formulation) in the space provided below the table. For calculations, the climate scientist has suggested that you translate the yearly percentage of CO<sub>2</sub> removed values (in percentage of CO<sub>2</sub> per year) into the lifetime that CO<sub>2</sub> stays in the atmosphere (in years).

Pairs		Rank (1 to 5)
From	To	
0.3% per year now	0.1% per year in future	
0.8% per year now	0.5% per year in future	
2.2% per year now	1.1% per year in future	
0.9% per year now	0.2% per year in future	
2.1% per year now	1.2% per year in future	

Please clearly show your work i.e. the math you did for getting the ranks in the table above (you are allowed to use a computer screen calculator for any calculations):

**Figure 5-2. The climate problems, Linear and Nonlinear, presented to the participants in the Aid condition. The same problems were presented in the no-Aid condition, except that the statement instructing the participant to convert the percent-removed to CO<sub>2</sub>'s lifetime was omitted.**

The ranks and math shown by participants were used to classify the type of procedure they used to respond (linear or nonlinear). Only one sequence of ranks from 1 to 5 is correct response in each problem, however, participants could enter different sequence of ranks by following different rank-order rules. Table 5-1 provides five different linear rank-order rules that participants could follow in each problem (numbered from 1 to 5) as a result of linear thinking. We made use of these five rules to classify a participant's ranking as being a linear response. The From and To values are given to participants (in Figure 5-2). The next three columns: "Proportional Change," "Delta Change," and "Correct Change in Years" are used to calculate five possible linear rules: "Correct Rule," "Difference Rule," "Addition Rule," "Ratio Rule," and

"Proportional Rule." Proportional Change refers to the relative change in the percent-removed given by the formula  $(\text{From} - \text{To}) / \text{From}$ . Delta Change refers to the difference between the From and To values of a percent-removed range. Correct Change in Years refers to the correct values of CO<sub>2</sub> lifetime that could be obtained by using the formula,  $100/\text{To} - 100/\text{From}$ .

The Correct Rule was the correct rank order obtained through the Correct Change in Years column. The other four rules represent different forms of linear-thinking response: the Difference Rule is the rank order obtained based on the Delta Change column; the Addition Rule is the rank order obtained by the addition of From and To values; the Ratio Rule is the rank order obtained based on the ratio of From/To; and the Proportional Rule is the rank order obtained using Proportional Change. In the Linear problem, all of the other four rank-order rules are the same as the Correct Rule (or correct response), but not in the Nonlinear problem.

Participants' responses were classified according to the rule they appeared to follow, or as "other" if their ranks did not correspond to any of the five linear rules (i.e., their responses were nonlinear-incorrect responses). If a participant ranked according to linear response or the Correct Rule in the Linear problem, then this ranking would lead her to a correct response. In contrast, a participant could only get a correct response on the Nonlinear problem by following the Correct Rule. Therefore, following a linear response on the Nonlinear problem could not have produced a correct response.

**Table 5-1. Different linear rank orders of the percent-removed ranges in the Linear and Nonlinear problems.**

Linear Problem									
From	To	Proportional Change	Delta Change	Correct Change in Years	Correct Rule (1)	Difference Rule (2)	Addition Rule (3)	Ratio Rule (4)	Proportional Rule (5)
2.1	0.1	0.95	2.0	952	1	1	1	1	1
2.0	0.3	0.85	1.7	283	2	2	2	2	2
1.9	0.5	0.74	1.4	147	3	3	3	3	3
1.6	0.9	0.44	0.7	49	4	4	4	4	4
1.7	1.1	0.35	0.6	32	5	5	5	5	5

Nonlinear Problem									
From	To	Proportional Change	Delta Change	Correct Change in Years	Correct Rule (1)	Difference Rule (2)	Addition Rule (3)	Ratio Rule (4)	Proportional Rule (5)
2.2	1.1	0.50	1.1	46	4	1	5	3	3
0.9	0.2	0.78	0.7	389	2	3	2	1	1
2.1	1.2	0.43	0.9	36	5	2	4	4	4
0.3	0.1	0.67	0.2	667	1	5	1	2	2
0.8	0.5	0.38	0.3	75	3	4	3	5	5

## 5.5 Results

Two independent raters coded each participant's response as belonging to one of the five rank rules (given in Table 5-1) or as "other". Inter-rater reliability for the two independent raters revealed satisfactory amounts of agreement between the two, Kappa, Correct = 0.94 ( $p < 0.001$ ), 95% CI<sup>19</sup> (0.89, 1.00); Kappa, Difference = 0.97 ( $p < 0.001$ ), 95% CI (0.92, 1.00); Kappa, Addition = 1.00 ( $p < .001$ ), 95% CI (1.00, 1.00); Kappa, Ratio = 0.92 ( $p < 0.001$ ), 95% CI (0.81, 1.00); Kappa, Proportion = 0.92 ( $p < 0.001$ ), 95% CI (0.81, 1.00); and Kappa, Other = 0.93 ( $p < 0.001$ ), 95% CI (0.80, 1.00). These categorizations were used for subsequent analysis of responses after resolving any inconsistency between raters through direct meeting and active discussion.

### 5.5.1 Proportion of Linear Responses within each Problem (H1a)

To test H1a, we compared the proportion of linear responses to other (nonlinear) responses within the Linear and Nonlinear problems in the Aid and no-Aid conditions for policy and non-policy backgrounds. Table 5-2 shows the proportion of correct responses, linear responses, and other responses for participants in both problems and both conditions. A non-zero correct response in the Linear problem was only due to linear thinking, and there were 0% correct responses in the Nonlinear problem.

For participants with non-policy backgrounds, the proportion of linear responses was significantly greater than the proportion of other (nonlinear) responses, regardless of the problem or condition: In the Aid condition and Linear problem (84% > 16%):  $\chi^2(1) = 17.789$ ,  $p < .001$ ,  $r = .68$ ; In the Aid condition and Nonlinear problem (79% > 21%):  $\chi^2(1) = 12.737$ ,  $p < .001$ ,  $r = .58$ ; In the no-Aid condition and Linear problem (92% > 8%):  $\chi^2(1) = 35.280$ ,  $p < .001$ ,  $r = .84$ ;

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<sup>19</sup> 95% Confidence interval

and in the no-Aid condition and Nonlinear problem (88% > 12%):  $\chi^2(1) = 28.880, p < .001, r = .76$ . These results supports hypothesis H1a.

For participants with policy backgrounds, the proportion of linear responses was significantly greater than the proportion of other (nonlinear) responses in the no-Aid condition's Linear (80% > 20%) ( $\chi^2(1) = 7.200, p < .01, r = .60$ ) and Nonlinear problem (80% > 20%) ( $\chi^2(1) = 7.200, p < .01, r = .60$ ). However, there was no difference between the proportion of linear responses and other responses in the Aid condition's Linear and Nonlinear problem (Linear problem: linear response (62%) = other response (38%) with  $\chi^2(1) = 1.385, ns, r = .23$ ; Non-linear problem: linear response (54%) = other response (46%) with  $\chi^2(1) = 0.154, ns, r = .08$ ). Therefore, an aid helped participants with policy backgrounds to rely less on linear responses. Support for hypothesis H1a is present in the problem without Aid, but not in the problem with Aid.

**Table 5-2. Proportion of participants following a correct, linear, and other response in the experiment.**

Response	Policy Backgrounds				Non-policy Backgrounds			
	Aid		No-Aid		Aid		No-Aid	
	Linear (%)	Nonlinear (%)	Linear (%)	Nonlinear (%)	Linear (%)	Nonlinear (%)	Linear (%)	Nonlinear (%)
Correct	62	00	50	00	63	00	72	00
Linear	62	54	80	80	84	79	92	88
Other	38	46	20	20	16	21	08	12

### 5.5.2 Proportion of Correct and Linear Responses between Linear and Nonlinear Problems (H1b)

To test H1b, we compared the proportion of correct responses between each problem in each condition for policy and non-policy backgrounds, respectively. For non-policy backgrounds, the proportion of correct responses was significantly greater for the Linear problem compared to the Nonlinear problem in both conditions (see Table 5-2) (Aid: 63% > 0% with  $\chi^2$

(1) = 17.538,  $p < .001$ ,  $r = .68$ ; no-Aid: 72% > 0% with  $\chi^2(1) = 28.125$ ,  $p < .001$ ,  $r = .75$ ).

Similarly, for policy backgrounds, the proportion of correct responses was significantly greater for the Linear problem compared to the Nonlinear problem in both conditions (Aid: 62% > 0% with  $\chi^2(1) = 13.765$ ,  $p < .001$ ,  $r = .73$ ; no-Aid: 50% > 0% with  $\chi^2(1) = 6.667$ ,  $p < .01$ ,  $r = .58$ ).

These results support H1b.

Furthermore, regardless of the background, the proportion of participants giving linear responses was no different between each problem in both conditions (see Table 5-2) (For non-policy background: Aid: 84% = 79% with  $\chi^2(1) = 0.175$ ,  $ns$ ,  $r = .07$ ; no-Aid: 92% = 88% with  $\chi^2(1) = 0.222$ ,  $ns$ ,  $r = .07$ . For policy background: Aid: 62% = 54% with  $\chi^2(1) = 0.158$ ,  $ns$ ,  $r = .08$ ; no-Aid: 80% = 80% with  $\chi^2(1) = 0.000$ ,  $ns$ ,  $r = .00$ ). These results show that the difference in correct responses between problems was due to the participants' persistent reliance on linear reasoning, regardless of their backgrounds and any aid.

### **5.5.3 Proportion of Correct and Linear Responses Between Aid and No-Aid Conditions (H2)**

To test H2, we compared the proportion of correct responses between the Aid and no-Aid conditions in the Linear and Nonlinear problems for non-policy and policy backgrounds. Aid had no effect on the proportion of correct responses in the Linear problem (for non-policy background: Aid: 63% = no-Aid: 72% with  $\chi^2(1) = 0.389$ ,  $ns$ ,  $r = .09$ ; for policy background: Aid: 62% = no-Aid: 50% with  $\chi^2(1) = 0.878$ ,  $ns$ ,  $r = .20$ ) or in the Nonlinear problem (for non-policy background: Aid: 0% = no-Aid: 0% with  $\chi^2(1) = \text{no-statistic}^{20}$ ,  $ns$ ,  $r = \text{no-statistic}$ ; for policy background: Aid: 0% = no-Aid: 0% with  $\chi^2(1) = \text{no-statistic}$ ,  $ns$ ,  $r = \text{no-statistic}$ ). Again, Aid had no effect on the proportion of linear responses in the Linear problem (for non-policy

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<sup>20</sup> Because there is no participant in the Nonlinear problem who gave a correct response, there is no statistic to report for the comparison due to the absence of data.

background: Aid: 84% = no-Aid: 92% with  $\chi^2(1) = 0.650$ , *ns*,  $r = .12$ ; for policy background: Aid: 62% = no-Aid: 80% with  $\chi^2(1) = 0.910$ , *ns*,  $r = .20$ ) or in the Nonlinear problem (for non-policy background: Aid: 79% = no-Aid: 88% with  $\chi^2(1) = 0.661$ , *ns*,  $r = .12$ ; for policy background: Aid: 54% = no-Aid: 80% with  $\chi^2(1) = 1.704$ , *ns*,  $r = .27$ ). Thus, Aid had no influence on participants' reliance on linear or correct responses. These results do not support hypothesis H2.

### 5.5.4 Effects of Educational Backgrounds

Finally, to test hypothesis H3, we compared the proportion of correct responses between policy and non-policy backgrounds in each problem in the Aid and no-Aid conditions, respectively. Overall, there was no difference for participants with policy and non-policy backgrounds. This finding holds in the Aid condition for the Linear problem (Correct response: 62% = 63% with  $\chi^2(1) = 0.126$ , *ns*,  $r = .06$ ; Linear response: 62% = 84% with  $\chi^2(1) = 2.116$ , *ns*,  $r = .26$ ) and for the Nonlinear problem (Correct response: 0% = 0% with  $\chi^2(1) = \text{no-statistic}$ , *ns*,  $r = \text{no-statistic}$ ; Linear response: 54% = 79% with  $\chi^2(1) = 2.264$ , *ns*,  $r = 0.27$ ). This finding also holds in the no-Aid condition for the Linear problem (Correct response: 50% = 72% with  $\chi^2(1) = 1.534$ , *ns*,  $r = .21$ ; Linear response: 80% = 92% with  $\chi^2(1) = 1.016$ , *ns*,  $r = .17$ ) and for the Nonlinear problem (Correct response: 0% = 0% with  $\chi^2(1) = \text{no-statistic}$ , *ns*,  $r = \text{no-statistic}$ ; Linear response: 80% = 88% with  $\chi^2(1) = 0.373$ , *ns*,  $r = .10$ ). When taken together, these results do not support hypothesis H3.

### 5.6 General Discussion

This research shows that people's linear thinking is pervasive while making judgments in nonlinear environmental problems. Our manipulation of aligning correct responses with linear thinking proved highly effective. Changing the information in the problem to align with a

person's dominant decision-making strategy (which in this case is responding linearly) can be an effective way of improving their decision making (Klayman & Brown, 1993; Payne et al., 1999). Moreover, an important point to note is that the information presentation manipulation does not change their thought processes in any way. The manipulation is simply meant to make use of these linear cognitive processes to help participants understand nonlinear problems in the way they naturally are inclined to and thus enable them to correctly respond. Furthermore, our results agree with prior evidence of linear thinking in environmental problems concerning inferences about CO<sub>2</sub> accumulation (Sterman, 2008; Sterman & Booth Sweeney, 2007).

Our results also indicate that a majority of participants with non-policy backgrounds responded linearly in problems with or without instructional aid and regardless of whether or not correct response was aligned with linear thinking. There could be a number of reasons for this overreliance amongst participants with non-policy backgrounds. First, it could simply be because linear responses are the simplest response to come to mind (Fischbein, 1999; Freudenthal, 1983; Lesh, Post, & Behr, 1988; Rouche, 1989). Second, literature has shown that even simple linear models lead to correct approximate responses in many cases that are more accurate than expert judgments (Dawes, 1979; Goldberg, 1970). Linear thinking offers two crucial benefits of being simple and/or it producing accurate and good enough answers in many problems, while avoiding more complicated nonlinear rules.

Furthermore, in our results, participants with policy backgrounds still relied on linear thinking and were not able to provide correct responses. But they were able to make some use of the instructional aid, which helped them to move away from linear thinking to other nonlinear or incorrect types of response. Although we can only currently speculate, one reason may be that it is challenging to *change* participants' cognitive thought processes to improve their decision

making (Klayman & Brown, 1993) and the aid was not inadequate in producing this change. A second reason could be on account of the aid's effectiveness itself: a descriptive aid that provided participants with the exact relationship between CO<sub>2</sub> lifetime and percent-removed might have been more effective. Still, participants with policy backgrounds, just like those with non-policy backgrounds, are limited by their cognitive capacity (Sterman & Booth Sweeney, 2007) and are thus unable to utilize the aid effectively. We plan to investigate these explanations as part of future research.

It is expected that the yearly percentage of CO<sub>2</sub> removed from the atmosphere will decrease in future years, resulting in a large increase in CO<sub>2</sub> lifetime (Cramer et al., 2001; Joos et al. 2001; Matear & Hirst, 1999; Sarmiento & Quéré, 1996). As this change will be detrimental to the earth's climate, accurate human assessment of the nonlinear relationship between the percent-removed and CO<sub>2</sub> lifetime is important. When participants were given a problem where a linear response would lead to an incorrect answer, none of the participants in the experiment correctly ranked the decreasing percent-removed ranges in the problem. They ultimately underestimate the most detrimental changes in CO<sub>2</sub> lifetime. This inaccurate assessment could be a possible reason for wait-and-see policies for climate change.

Finally, aligning a nonlinear problem with linear mental models is a manipulation that may also be useful in many other important problems. For example, an intervention similar to the one tested here could be attempted for reducing the dispersal of a commodity (e.g., pollution in river) by giving people choices about the taxes they pay per unit of dispersing the commodity. For example, consider a certain tax per kilogram on pollution created in a river (units: \$/Kg of pollution) aimed at reducing pollution. Polluters, like large industrial factories on the river's banks, could be offered different taxation choices, where they are charged with a smaller tax now

and a larger tax in the near future for each policy. A range of tax increases could be designed in such a way that the smallest increase for the same amount of total pollution appears the most attractive to polluters according to their linear thinking. But in fact, the smallest increase has the maximum potential to reduce river pollution. Our future endeavor in this research will be to extend the information presentation manipulation to other nonlinear problems faced in daily life.

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## **Chapter 6: Using Cognitive Factors to Improve Environmental Decisions – Application to Eco-taxes**

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### **Enabling eco-friendly choices by relying on the proportional-thinking heuristic**

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## 6.1 Abstract

Ecological (eco) taxes are promising mechanisms to enable eco-friendly decisions but few people would like to pay them. In this study, we present a way in which eco-tax options may be communicated to general public to encourage their payment. The suggested implementation (called “information presentation”) takes advantage of the non-linear relationship between eco-tax payments and CO<sub>2</sub> emissions, and the human reliance on the proportional-thinking heuristic. According to the proportional-thinking heuristic, people are likely to prefer a small increase in eco-tax and judge larger eco-tax increases to cause proportionally greater reductions in CO<sub>2</sub> emissions. In an online study, participants were asked to choose between two eco-tax increases in two decision problems: In one, a smaller eco-tax increase resulted in greater CO<sub>2</sub> emissions reduction, while in the other, a smaller tax increase resulted in lesser CO<sub>2</sub> emissions reduction. Although the larger eco-tax increase in one of the problems did not reduce CO<sub>2</sub> emissions the most, across both problems, people judged larger eco-tax increases to cause proportionally greater reductions in CO<sub>2</sub> emissions and preferred smaller tax increases. Thus, eco-tax policies are likely to benefit from presenting information in terms of eco-tax increases, such that smaller eco-tax increases (which are more attractive and are likely to be chosen by people) cause greater CO<sub>2</sub> emissions reductions.

*Keywords:* Proportional thinking; Eco-tax; Climate change; Carbon-dioxide emissions

## 6.2 Introduction

Literature on human decision making broadly demonstrates that humans rely upon a number of heuristics (Gilovich et al. 2002). Many of these heuristics might adversely affect human decision making on important global problems (e.g., climate change). To improve human decisions, one option is to design manipulations that make humans aware and help them overcome their reliance on heuristics; however, another and perhaps easier manipulation is to present information in a way that people's reliance on heuristics improves their decisions (Johnson et al. 1988; Klayman and Brown 1993; Payne et al. 1999). In this paper, we follow the latter approach and show how information about ecological (eco) tax increases may be presented such that this presentation takes advantage of people's reliance on a "proportional-thinking" heuristic and enables them to make choices that result in larger reductions in CO<sub>2</sub> emissions. Furthermore, we discuss that our information-presentation manipulation may be used to improve people's decision choices in many other societal problems (e.g., cigarette smoking, pollution in rivers, air pollution, and overfishing).

An eco-tax (or carbon price) is the cost people would pay to emit a unit of CO<sub>2</sub> in the atmosphere (units: \$/ton of CO<sub>2</sub> emissions or \$/ton). Eco-taxes are promising economic mechanisms to enable eco-friendly decisions – decisions that reduce carbon-dioxide (CO<sub>2</sub>) emissions in the atmosphere and mitigate climate change (Carbon Tax Center (CTC) 2010; Dawson and Spannagle 2009; Nordhaus 2008; Stern 2006). Yet, very few people would likely to agree to pay eco-taxes to reduce CO<sub>2</sub> emissions on account of their reliance on heuristics. One of these heuristics is called *proportional thinking*, according to which, people assume a strong positive correlation between a problem's independent (input) and dependent (output) variables (Booth Sweeney and Sterman 2000; Cronin and Gonzalez 2007; Cronin et al. 2009; Dörner

1996; Dutt and Gonzalez 2009, 2011; Larrick and Soll 2008; Van Dooren et al. 2007). For example, by relying on the proportional-thinking heuristic for the Earth's climate people might wrongly infer that the shape of CO<sub>2</sub> concentration (output) over time should be identical to the shape of the CO<sub>2</sub> emissions (input) (Dutt and Gonzalez, 2011; Sterman and Booth Sweeney 2002, 2007; Sterman 2008). Therefore, if CO<sub>2</sub> emissions are assumed to increase linearly over time<sup>21</sup>, then by relying on proportional thinking people will infer a linear increasing shape for the atmospheric CO<sub>2</sub> concentration that is similar to the shape of CO<sub>2</sub> emissions. Consequently, such linear judgments are likely to make people underestimate the actual nonlinear increase in CO<sub>2</sub> concentration, undermine the seriousness of the climate problem, and cause them to defer acting on climate change (Dutt 2011).

People's reliance on the proportional-thinking heuristic is likely to be present for their decisions about eco-tax payment preferences and judgments. For example, by relying on the proportional-thinking heuristic, people are likely to prefer smaller tax increases, while associating larger tax increases to mean *proportionally* greater benefits or reductions in CO<sub>2</sub> emissions. An evidence for this belief comes from the marketing literature. For example, most shoppers believe that higher prices are a sign of greater product quality and repeated studies have shown that while shopping people expect more expensive products to be beneficial or better in quality (Dodds et al. 1991; Plassman et al. 2007; Rao and Monroe, 1989). A recent evidence of this finding comes from Plassman et al. (2007), who told their participants that they were drinking five different varieties of wine and disclosed the prices for each as participants drank. In practice, the participants were only consuming three different wines since two were offered twice: a \$5 wine described as costing \$5 and \$45, and a \$90 bottle presented as \$90 and \$10.

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<sup>21</sup> An assumption of a linear increase in CO<sub>2</sub> emissions over time serves as a good approximation to their pattern of actual increase over the last 20 years (IPCC 2007).

(There was also a \$35 wine with the accurate price.) People rated identical wines as tasting better when they were priced higher (e.g., \$45) and fMRI scans showed greater activity in the brain's pleasure regions.

According to the proportional-thinking heuristic, given a range of options for eco-tax payments to choose between and due to people's tendency to avoid the displeasure of paying higher taxes (Plassman et al. 2007), people are likely to prefer an option with the smallest possible tax increase. Indeed, there is some real world evidence to support this expectation. For example, in a large poll conducted in the U.S. (N>600), only 17% of respondents preferred an increase in carbon taxes (Leiserowitz 2003, 2007). Similarly, when the French President Nicolas Sarkozy recently scrapped a planned carbon tax, 69% of respondents endorsed his decision, while only 21% said that it was wrong (N=948) (Kennedy 2011).

In addition, for eco-tax payments and the corresponding CO<sub>2</sub> emission reductions, relying on proportional-thinking thinking means that people believe that larger eco-tax increases will result in proportionally greater CO<sub>2</sub> emissions reductions (i.e., benefits) compared to smaller increases. For example, under the 2009 America's Energy Security Trust Fund Act, a yearly \$10/ton increase in carbon tax was believed by Congressmen to result in a *proportional* 31% reduction in CO<sub>2</sub> emissions below their 2005 level. Thus, policymakers including laypeople are likely to believe that *larger* tax increases are also those that result in *greater* reductions of CO<sub>2</sub> emissions.

The problem with applying the proportional-thinking heuristic to eco-taxes is that it is not true that larger eco-tax increases result in greater CO<sub>2</sub> emissions reductions. According to the IPCC (2007), there is considerable uncertainty and difficulty in determining the base tax (in \$/ton of CO<sub>2</sub> emissions in the atmosphere) for eco-taxes (believed to vary between \$3/ton to

\$95/ton). A suggested method is to allow people to choose between multiple tax increases with different base taxes (Metcalf and Weisbach 2009). For example, suppose a person has a budget constraint of \$100 for eco-taxes each month.<sup>22</sup> Under this scenario, a \$6/ton tax increase from a base tax of \$18/ton tax would reduce this person's emissions by 1.39 tons ( $=100*(1/18 - 1/24)$ ). However, a smaller \$3/ton increase from a smaller base tax of \$13/ton would reduce his emissions by 1.44 tons. Thus, in this case, the smaller base tax with a smaller tax increase is associated with a greater reduction of CO<sub>2</sub> emissions, in contrast to proportional-thinking heuristic.

Therefore, by relying on the proportional-thinking heuristic, people are likely to prefer smaller base tax with the smaller increase over larger base tax with the larger increase, and are likely to judge larger base tax with the larger increase to reduce CO<sub>2</sub> emissions the most. The main idea that we demonstrate in this paper is that a proper presentation of eco-taxes and their increases is likely to enable more eco-friendly choices while people continue to associate larger tax increases with greater CO<sub>2</sub> emissions reductions. Prior research in human psychology shows that a change in information presentation of a nonlinear mathematical problem can improve people's decisions in that problem (Johnson et al. 1988; Klayman and Brown 1993; Payne et al. 1999). We demonstrate the effectiveness of this information-presentation manipulation with an experiment involving eco-taxes in the next section.

### **6.3 Method**

In order to test people's tax preferences with respect to their judgments about CO<sub>2</sub> emissions reductions, we ran an online experiment using two problems: One in which reliance on the proportional-thinking heuristic is likely to cause more eco-friendly preferences and is likely

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<sup>22</sup> It is common to find that a majority of families with monthly wages or income have such budgetary constraints which limit their spending on products they could purchase (Gale, 2011).

to hamper correct judgments about CO<sub>2</sub> emissions reductions; and the other, where reliance on the proportional-thinking heuristic is likely to support correct judgments about emissions reductions and is likely to cause less eco-friendly preferences.

### **6.3.1 Participants**

One hundred and sixty-five participants were recruited using Amazon's Mechanical Turk (MTurk). Based on self-reported demographics 54% were males; 40% held graduate degrees and the other 60% held undergraduate and high-school degrees; and 67% had a background in science, technology, engineering, mathematics, or medicine (STEM). Ages ranged from 18 to 55 years ( $M = 25$ ,  $S.D. = 8$ ). No participant took more than 5 minutes to complete the experiment, and each participant was paid €5. The payment amount is considered standard for studies of this length on MTurk (Mason and Suri 2010; Paolacci et al. 2010).

### **6.3.2 Material**

Two problems, P1 and P2, each involving a choice between two options were presented in a within-subjects design to participants. The order of presentation of the two options (left or right) was randomized within each problem, and the two options that appeared together in a problem were also randomized across the two problems. Both options in a problem involved an increase of a carbon-price from the "From" price this month to the "To" price next month and were designed such that a smaller carbon-price increase with a smaller base tax was tied to either greater or less CO<sub>2</sub> emissions reduction. For example, depending upon the random assignment of options across the two problems, if the option with a smaller carbon-price increase reduced greater CO<sub>2</sub> emissions in P1, then the option with the smaller price increase reduced less CO<sub>2</sub> emissions in P2.

Figure 6-1 shows the problems given to participants. Given a budget constraint of \$100 per month for tax payment, P1's option 1 reduces CO<sub>2</sub> emissions by  $(1/18 - 1/24)*\$100=1.39$  tons with a price increase of \$6/ton, and P1's option 2 by  $(1/13 - 1/16)*\$100=1.44$  tons with a price increase of \$3/ton. Therefore, P1's option 1 is a greater carbon-price increase that results in less CO<sub>2</sub> emissions reduction (costly eco-adverse), and P1's option 2 is a low carbon-price increase that results in greater CO<sub>2</sub> emissions reduction (cheap eco-friendly). In contrast, P2's option 1 reduces CO<sub>2</sub> emissions by  $(1/19 - 1/25)*\$100=1.26$  tons with a price increase of \$6/ton, and P2's option 2 by  $(1/15 - 1/18)*\$100=1.11$  tons with a price increase of \$3/ton. Therefore, P2's option 1 involves a high carbon-price increase that results in greater CO<sub>2</sub> emissions reduction (costly eco-friendly), and P2's option 2 involves a low carbon-price increase that results in less CO<sub>2</sub> emissions reduction (cheap eco-adverse). Moreover, the ranges and values of carbon-prices (\$/ton) given as part of the two options in each of the two problems is representative of the actual anticipated eco-taxes in the real world (IPCC 2007; Metcalf and Weisbach 2009).

For each problem, participants were asked two questions. The first question (Q1, preference question) asked participants to choose one of the two options that they preferred. The second question (Q2, reduction-judgment question) gave participants a fixed personal tax-payment budget (=\$100 per month) and asked them to choose the option that they thought would reduce CO<sub>2</sub> emissions the most. In Q1, we expected participants to prefer the cheap eco-friendly and cheap eco-adverse options, while we expected participants to simultaneously judge the costly eco-friendly and costly eco-adverse options as reducing CO<sub>2</sub> emissions the most for Q2.

### Problem (P1)

To help mitigate the effects of global warming, the government is considering charging you a monthly carbon price for your carbon-dioxide emissions and wants to evaluate your preferences. The government has given you two options: option 1 and option 2 (see below). The From and To values associated with each option represent the price in dollars for **each ton** of carbon-dioxide that you emit to the atmosphere (i.e., \$/ton). In each option, you would start by paying the amount in the From carbon price right now, i.e., this month; but, this amount will increase to the To carbon price from the next month on. Please answer the following questions:

Option 1 ( <i>costly eco-adverse</i> )		Option 2 ( <i>cheap eco-friendly</i> )	
From carbon price (\$/ton)	To carbon price (\$/ton)	From carbon price (\$/ton)	To carbon price (\$/ton)
\$18	\$24	\$13	\$16

(Preference Question)

Q1. Circle your preferred option:      Option 1      Option 2

(Reduction-judgment Question)

Q2. Suppose that you have a personal tax budget of \$100 for this month and \$100 for the next month (i.e., after the increase in price). Which of the two options (option 1 or option 2) will result in the most reduction in your carbon-dioxide emissions in the next month compared to this month?

Please circle your preference:    Option 1      Option 2

### Problem (P2)

The government reconsidered the options that it gave you before and now it wants you to express your preference in two new options (see below). The From and To values associated with each option represent the price in dollars for **each ton** of carbon-dioxide that you emit to the atmosphere (i.e., \$/ton). In each option, you would start by paying the amount in the From carbon price right now, i.e., this month; but, this amount will increase to the To carbon price from the next month on. Please answer the following questions:

Option 1 ( <i>costly eco-friendly</i> )		Option 2 ( <i>cheap eco-adverse</i> )	
From carbon price (\$/ton)	To carbon price (\$/ton)	From carbon price (\$/ton)	To carbon price (\$/ton)
\$19	\$25	\$15	\$18

(Preference Question)

Q1. Circle your preferred option:      Option 1      Option 2

(Reduction-judgment Question)

Q2. Suppose that you have a personal tax budget of \$100 for this month and \$100 for the next month (i.e., after the increase in price). Which of the two options (option 1 or option 2) will result in the most reduction in your carbon-dioxide emissions in the next month compared to this month?

Please circle your preference:    Option 1      Option 2

**Figure 6-1. The two problems, P1 and P2, given to participants in the experiment. Each problem involved two options, option 1 and 2, and two questions, question 1 and 2. The order of the presentation of the two options (left or right) was randomized within each problem and the two options that appeared together in a problem were also randomized across the two problems. Question 1 asked people their preference for one of the two options. Question 2 gave people a tax budget of \$100 per month and asked them to judge which option reduced most CO<sub>2</sub> emissions in the atmosphere. The order of presentation of questions in each problem was first question 1 and then followed by question 2. The text in italics was not provided to participants and has been solely placed to aid in understanding of the material.**

### **6.3.3 Procedure**

The problems were administered through a website online, with participants answering both questions in both problems. Only one problem was presented at a time. MTurk was used to recruit and compensate participants. Participants read an advertisement about an eco-tax study and were asked to click a link to participate.

### **6.4 Results**

We compared the proportions of cheap and costly choices, and the proportions of eco-friendly and eco-adverse choices in the preference question (Q1) aggregated across the two problems (see Table 6-1a). The proportion of cheap choices (70%) was greater than costly choices (30%) ( $\chi^2(1)=108.824, p<.001, r=.41$ ); but, there was no difference between the proportions of eco-friendly choices (48%) and eco-adverse choices (52%) ( $\chi^2(1)=1.552, ns, r=.05$ ): showing participants' preferences for smaller tax increases to be irrespective of whether the increase reduced greater or lesser CO<sub>2</sub> emissions.

When comparing individual preferences in Table 6-1b, the proportions of cheap eco-friendly choices (68%) and cheap eco-adverse choices (73%) were greater than the proportions of costly eco-adverse choices (32%) and costly eco-friendly choices (27%), respectively (cheap eco-friendly>costly eco-adverse:  $\chi^2(1)=42.194, p<.001, r=.36$ ; cheap eco-adverse>costly eco-friendly:  $\chi^2(1)=68.182, p<.001, r=.46$ ). Furthermore, the proportions of cheap eco-friendly

choices and cheap eco-adverse choices, and proportions of costly eco-friendly choices and costly eco-adverse choices were not significantly different ( $\chi^2(1)=0.929$ , *ns*,  $r=.05$ ). Consistent with proportional-thinking heuristic, these results suggest that participants preferred the cheap options, irrespective of the actual reductions in CO<sub>2</sub> emissions.

We performed similar comparisons between choices, but now for the reduction-judgment question (Q2). For the reduction-judgments in Table 6-1c, the proportion of costly choices (67%) was greater than the proportion of cheap choices (33%) ( $\chi^2(1)=73.333$ ,  $p<.001$ ,  $r=.33$ ); but there was no difference between proportions of eco-friendly choices (52%) and eco-adverse choices (48%) ( $\chi^2(1)=0.873$ , *ns*,  $r=.04$ ): showing participants implicitly assumed that larger tax increases would reduce CO<sub>2</sub> emissions the most, irrespective of whether or not they actually reduced CO<sub>2</sub> emissions. Upon comparing individual judgments for the reduction-judgment question in Table 6-1d, the proportions of costly eco-adverse choices (65%) and costly eco-friendly choices (68%) were greater than the proportions of cheap eco-friendly choices (35%) and cheap eco-adverse choices (32%), (costly eco-adverse>cheap eco-friendly:  $\chi^2(1)=29.103$ ,  $p<.001$ ,  $r=.30$ ; costly eco-friendly>cheap eco-adverse:  $\chi^2(1)=45.103$ ,  $p<.001$ ,  $r=.37$ ). Moreover, the proportions of costly eco-friendly and costly eco-adverse choices, and proportions of cheap eco-friendly and cheap eco-adverse choices were not significantly different ( $\chi^2(1) = 0.491$ , *ns*,  $r = .04$ ). Consistent with proportional thinking, these results suggest that participants judged the costly options to reduce CO<sub>2</sub> emissions the most, irrespective of the actual reductions.

**Table 6-1a. Proportion of choices across the two problems for preferences.**

	<i>Costly</i>	<i>Cheap</i>
Preference (Q1)	30% (N=98/330 <sup>1</sup> )	70% (N=232/330)
	<i>Eco-friendly</i>	<i>Eco-adverse</i>
Preference (Q1)	48% (N=157/330)	52% (N=173/330)

*Note.* <sup>1</sup>This number is double the total number of participants in the experiment because it is aggregated across both problems that were presented within-subjects and that contained N=165 participants each.

**Table 6-1b. Proportion of choices for preferences.**

<i>Questions</i>	<i>Costly Eco-adverse</i> (6 unit increase; 1.39 tons CO <sub>2</sub> emissions reduction)	<i>Cheap Eco-friendly</i> (3 unit increase; 1.44 tons CO <sub>2</sub> emissions reduction)	<i>Costly Eco-friendly</i> (6 unit increase; 1.26 tons CO <sub>2</sub> emissions reduction)	<i>Cheap Eco-adverse</i> (3 unit increase; 1.11 tons CO <sub>2</sub> emissions reduction)
Preference (Q1)	32% (N=53/165 <sup>1</sup> )	68% (N=112/165)	27% (N=45/165)	73% (N=120/165)

*Note.* <sup>1</sup>This number represents the total number of participants in the experiment.

**Table 6-1c. Proportion of choices across the two problems for reduction-judgments.**

	<i>Costly</i>	<i>Cheap</i>
Reduction-judgment (Q2)	67% (N=220/330 <sup>1</sup> )	33% (N=110/330)
	<i>Eco-friendly</i>	<i>Eco-adverse</i>
Reduction-judgment (Q2)	52% (N=171/330)	48% (N=159/330)

*Note.* <sup>1</sup>This number is double the total number of participants in the experiment because it is aggregated across both problems that were presented within-subjects and that contained N=165 participants each.

**Table 6-1d. Proportion of choices for reduction-judgments.**

<i>Questions</i>	<i>Costly Eco-adverse</i> (6 unit increase; 1.39 tons CO <sub>2</sub> emissions reduction)	<i>Cheap Eco-friendly</i> (3 unit increase; 1.44 tons CO <sub>2</sub> emissions reduction)	<i>Costly Eco-friendly</i> (6 unit increase; 1.26 tons CO <sub>2</sub> emissions reduction)	<i>Cheap Eco-adverse</i> (3 unit increase; 1.11 tons CO <sub>2</sub> emissions reduction)
Reduction-judgment (Q2)	65% (N=107/165 <sup>1</sup> )	35% (N=58/165)	68% (N=113/165)	32% (N=52/165)

*Note.* <sup>1</sup>This number represents the total number of participants in the experiment.

### **6.4.1 Consistency between Preferences and Reduction-judgments**

Next, we determined how people's reduction-judgments (Q2) matched with their preferences (Q1). As shown in Table 6-2, 44% of participants simultaneously preferred cheap options and judged costly options as reducing CO<sub>2</sub> emissions the most, while only 7% of participants simultaneously preferred costly options and judged cheap options as reducing emissions the most. This pattern of choices for costly and cheap options seems to be consistent with reliance on proportional-thinking heuristic in preferences and judgments about CO<sub>2</sub> emissions reductions, respectively. In addition, the proportion for simultaneous preferences and judgments about CO<sub>2</sub> emissions reductions were comparatively smaller for the Costly-Costly and Cheap-Cheap choice combinations (see Table 6-2). Moreover, preferences for eco-friendly or eco-adverse options and simultaneous reduction-judgments for eco-friendly or eco-adverse options were about the same in all choice combinations. These results show that people decided primarily based upon options being costly or cheap, irrespective of whether their choices reduced greater or less CO<sub>2</sub> emissions.

### **6.4.2 Consistency of Preferences and Reduction-judgments Between the Two Problems**

As shown in Table 6-3, 63% preferred cheap options in both problems, while the proportion of preferences were comparatively smaller for the following combination of options across the two problems: cheap in the first problem and costly in the second problem, costly in the first problem and cheap in the second problem, and cheap in both problems. Similarly in Table 6-4, 55% judged costly options in both problems to reduce CO<sub>2</sub> emissions the most, while the proportion of reduction-judgments were comparatively smaller for the following combination of options across the two problems: costly in the first problem and cheap in the second problem,

cheap in the first problem and costly in the second problem, and cheap in both problems. These results show that participants were pretty consistent about their preferences for cheap options and reduction-judgments for costly options across the two problems, irrespective of whether their preferences and reduction-judgments reduced greater or less emissions.

### **6.4.3 Are Preferences Based on Options being Eco-friendly or Cheap?**

In our results, a large majority (68%) of participants preferred the cheap eco-friendly option (see Table 6-1). A possible explanation for this 68% (=112/165) preference is that it is based on the option being eco-friendly rather than it being cheap. The cheap eco-friendly option boasts a small carbon-price increase (=3 units), but also reduces CO<sub>2</sub> emissions most (=1.44 tons) at the same time. However, 60% (=68/112) of those that preferred the cheap eco-friendly option also judged the costly eco-adverse option to save more CO<sub>2</sub>. Furthermore, 92% (=103/112) of those that preferred the cheap eco-friendly option also judged the cheap eco-adverse option as reducing CO<sub>2</sub> emissions the most in the next problem. In both judgments, the costly or cheap eco-adverse options do not reduce CO<sub>2</sub> emissions the most and thus these options are not eco-friendly. Therefore, a closer inspection of results reveals that the 68% of cheap eco-friendly preferences represented participants that were relying on proportional-thinking heuristic and driven by selecting a cheap option, rather than participants that acted because the option was eco-friendly.

**Table 6-2. Participants' proportion of reduction-judgments with respect to their proportion of preferences within problems.**

Reduction-judgment (Q2)	Preference (Q1)			
	<i>Costly</i> (N=98)	<i>Cheap</i> (N=232)	<i>Eco-friendly</i> (N=157)	<i>Eco-adverse</i> (N=173)
<i>Costly</i> (N=220)	23% (N=76/330 <sup>1</sup> )	44% (N=144/330)		
<i>Cheap</i> (N=110)	7% (N=22/330)	26% (N=88/330)		
<i>Eco-friendly</i> (N=171)			25% (N=81/330)	27% (N=90/330)
<i>Eco-adverse</i> (N=159)			23% (N=76/330)	25% (N=83/330)

*Note.* <sup>1</sup>This number is double the total number of participants in the experiment because it is aggregated across both problems that were presented within-subjects and that contained N=165 participants each.

**Table 6-3. Participants' proportion of preferences across the first and second presented problems.**

Second Presented Problem's Preference (Q1)	First Presented Problem's Preference (Q1)	
	<i>Costly</i> (N=48)	<i>Cheap</i> (N=117)
<i>Costly</i> (N=50)	22% (N=36/165 <sup>1</sup> )	8% (N=14/165)
<i>Cheap</i> (N=115)	7% (N=12/165)	63% (N=103/165)

*Note.* <sup>1</sup>This number represents the total number of participants in the experiment.

**Table 6-4. Participants' proportion of reduction-judgments in the first and second presented problems.**

Second Presented Problem's Reduction-judgment (Q2)	First Presented Problem's Reduction-judgment (Q2)	
	<i>Costly</i> (N=112)	<i>Cheap</i> (N=53)
<i>Costly</i> (N=108)	55% (N=91/165 <sup>1</sup> )	10% (N=17/165)
<i>Cheap</i> (N=57)	13% (N=21/165)	22% (N=36/165)

*Note.* <sup>1</sup>This number represents the total number of participants in the experiment.

#### **6.4.4 Are Preferences Driven by Accumulated CO<sub>2</sub> Reductions or Choice for the Cheaper Option?**

We believe that people's preference for cheap options is likely due to their displeasure of incurring a greater loss due to tax payment. But as we simply asked people which option they *preferred*, one possibility could be that they prefer a smaller increase with a smaller base tax because the smaller increase causes the most *accumulated* CO<sub>2</sub> reductions over the two months compared to the larger tax increase.<sup>23</sup> For example, smaller tax increases like \$13/ton to \$16/ton

<sup>23</sup> Accumulated CO<sub>2</sub> reduction is Budget/Tax rate this month + Budget/Tax rate next month. For example, for a \$100 budget, a change from \$13/ton to \$16/ton leads to 100/13 + 100/16 = 13.9 tons of accumulated CO<sub>2</sub> reduction.

and \$15/ton to \$18/ton cause greater CO<sub>2</sub> reductions of 13.9 tons and 12.2 tons, respectively, compared to those for larger tax increases like \$18/ton to \$24/ton (=9.7 tons) and \$19/ton to \$25/ton (=9.3 tons), respectively. In order to test this possibility, we ran an identical study with N=155 participants;<sup>24</sup> however, where we now changed one problem to be a choice between an increase from \$19/ton to \$25/ton or an increase from \$21/ton to \$24/ton (the other problem with increases \$18/ton to \$24/ton and \$13/ton and \$16/ton was unchanged). The \$21/ton to \$24/ton increase is a small 3 units increase, but the accumulated CO<sub>2</sub> reduction in this increase equals 8.9 tons, which is less than that in the \$19/ton to \$25/ton increase (=9.3 tons). If people decided according to accumulated CO<sub>2</sub> reductions, then fewer people should have chosen the smaller increase; however, results indicated that 63% of participants still chose the smaller tax increase (\$21/ton to \$24/ton), thereby preferring the cheaper option.

## 6.5 Conclusions

We find that consistent with proportional-thinking heuristic, people prefer smaller rather than larger eco-tax increases while simultaneously judging larger increases as reducing CO<sub>2</sub> emissions more, consistent with proportional-thinking heuristic. Furthermore, we demonstrated how one could make use of the proportional-thinking heuristic to enable participants to make more eco-friendly choices: when participants are provided with ranges of tax increases, they prefer smaller increases and their preference can result in greater CO<sub>2</sub> reductions, depending on how information is presented.

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<sup>24</sup> The procedure and experimental design in this new study were identical to those reported for the original study. In the new study 155 participants were recruited using Amazon's Mechanical Turk (MTurk). Based on self-reported demographics 55% were males; 50% held graduate degrees and the other 50% held undergraduate and high-school degrees; and 70% had a background in science, technology, engineering, mathematics, or medicine (STEM). Ages ranged from 18 to 50 years (M = 19, S.D. = 4). No participant took more than 5 minutes to complete the new study, and each participant was paid €5.

People's preferences for smaller eco-taxes is likely due to proportional-thinking heuristic (Kahneman and Tversky 1979; Slovic et al. 2004; Tversky and Kahneman 1991): people are likely to perceive that a larger increase with a larger base tax (e.g., \$18/ton to \$24/ton) will reduce their current wealth more and bring them greater displeasure (Dodds et al. 1991; Plassman et al. 2007; Rao and Monroe 1989). Furthermore, people's implicit reasoning of a proportional relationship between increases in eco-taxes and the corresponding increases in CO<sub>2</sub> emissions reductions is also likely driven by proportional-thinking heuristic. People are more likely to associate a larger eco-tax increase with a larger base tax as resulting in *proportionally* greater emissions reduction compared to a smaller increase with a smaller base tax. This reasoning is more so because we specifically asked people to choose the option with most CO<sub>2</sub> reduction next month *compared to* the reduction this month in the reduction-judgment question.

Therefore, people's reliance on the proportional-thinking heuristic can be used to enable more eco-friendly choices, even while people believe that they are saving money by preferring the smallest eco-tax increase. This manipulation does not require any change in people's psychological processes, but only a change in the way information is presented for decision making. This kind of manipulation is also effective in enabling improved judgments in other decision problems (Johnson et al. 1988; Klayman and Brown 1993; Payne et al. 1999). For example, Johnson et al. (1988) have shown that changing probability numbers from fractions (e.g., 29/36) to decimals (e.g., 0.8) caused people to make consistent choices for risky options in two lotteries that had the same expected value, but where the risky option had a small probability of a large outcome in one lottery and a large probability of a small outcome in the other. Similarly, changing the presentation of eco-taxes such that a smaller increase also reduces CO<sub>2</sub> emissions more will promote more eco-friendly decisions.

According to the CTC (2010), the current prices of gasoline, electricity, and fuels in most parts of the world include none of the costs associated with catastrophic climate change. This omission suppresses incentives to develop and deploy CO<sub>2</sub> reduction measures that are energy efficient (e.g., high-mileage cars, high-efficiency heaters, and air conditioners in homes). Conversely, taxing people's consumption of fuels according to their emissions will infuse these incentives at every link in the chain of decision and action — from individuals' choices and uses of vehicles, appliances, and housing. The main implication of our manipulation benefits eco-tax policies, provided policymakers present eco-friendly options as the ones that also offer smaller increases. By doing so, we expect that society's adoption of eco-friendly taxes will be more readily accepted, because people would not need to change their current behavior.

Although eco-tax is specifically used in this study, the applicability of our manipulation is broad and widespread given people's reliance on heuristics. A number of other important real-world problems (e.g., cigarette smoking, pollution in rivers, air pollution, and overfishing) could be improved by presenting information in a similar form. For example, the government could consider increasing tax per packet of cigarette to reduce smoking. One of the tax options could be a tax increase of a dollar, from \$1 per cigarette packet this month to \$2 per packet next month. Another option could be a tax increase of \$2, from \$3 per packet this month to \$5 per packet next month. If smokers spend on average a \$100 tax buying cigarettes each month, then the first option will reduce their consumption by 50 cigarette packets; while the latter option only by 13 packets. On account of proportional-thinking heuristic, we expect smokers to also readily prefer the option with \$1 tax increase compared to the \$2 tax increase. The end result would be a larger reduction in packets smoked – a desirable outcome. In the real world, it might be very difficult to change existent human behavior and reliance on heuristics (Klayman and Brown 1993). We

suggest an alternative: To change people's decision environment such that existent behavior and reliance on heuristics enables people to improve their decision choices.

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## **6.7 Next Chapters' Highlights**

The next two chapters in this thesis discuss people's risk- and time- preferences as important psychological factors influencing their wait-and-see choices. Here, probability, timing, and cost of future climate consequences are manipulated in a written description or as an actual experience. The effects of these manipulations are evaluated on people's wait-and-see choices.

## **Chapter 7: Decisions from Description and Experience: Effects of Probability and Timing of Climate Consequences**

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### **Why do we want to delay actions on climate change? Effects of probability and timing of climate consequences**

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## 7.1 Abstract

This research tests people's support for the "wait-and-see" approach in climate change due to the uncertainty in both the timing and probability of future consequences. In a laboratory experiment, carbon-tax consequences were presented to participants in one of two forms: a written description, where the probability, consequences, and timing were explicitly provided; and experience, where the probability, consequences, and timing were sampled through unlabeled buttons. Four problems were presented in each condition such that the probability of consequences was high or low and the timing was early or late. Results indicated that the proportion of wait-and-see choices was greater in experience than description. Furthermore, in both experience and description, the proportion of wait-and-see choices was greater when the probability was low rather than high. The difference in the proportion of wait-and-see choices between the low and high probability was amplified in experience and attenuated in description. Finally, there was no difference in the proportion of wait-and-see choices when the timing of climate consequences was early rather than late in both experience and description. These results are explained by people's risk and time preferences.

*Keywords:* time, probability, wait-and-see, decisions from experience, decisions from description, climate change

## 7.2 Introduction

Unlike other problems with risky outcomes, the problem of climate change is a global problem and one where consequences are both delayed and uncertain (Sterman, 2008; Weber, 2006). Despite the seriousness of the problem, a large number of people, including citizens, policy makers, and scientists, prefer to take risks and wait rather than act now on the problem's mitigation (i.e., they exhibit a “wait-and-see” approach to climate change) (Dutt & Gonzalez, 2011; Nordhaus, 1994; Sterman, 2008; Sterman & Booth Sweeney, 2002, 2007).

A 2007 U.N. survey found that a majority of respondents advocate a wait-and-see or go-slow approach to emission reductions (Leiserowitz, 2007; Sterman, 2008). This wait-and-see approach is directly related to people's risk-taking behavior: people that are more risk-taking also show more wait-and-see behavior toward climate change (Leiserowitz, 2006). Policymakers also seem to prefer to take risks: “slow the growth of greenhouse gas emissions, and—as the science justifies—stop, and then reverse that growth” (G. Bush, 2/14/02; Jones, 2002). In fact, the wait-and-see approach has been a predominant policy in the U.S., and as a result, the U.S. is the second highest emitter of CO<sub>2</sub> greenhouse gas in the world (i.e., 20% of world CO<sub>2</sub> emissions just after China) (Vidal & Adam, 2007). A comparison of the wait-and-see approach between the U.S. and E.U. reveals that a greater proportion of people express the need to act now on climate change in the E.U. than in the U.S. (Leiserowitz, 2007). In the E.U., the governments have already acknowledged a 20% decrease in emissions by the year 2020 and are now pressing for a 30% reduction in emissions, while the U.S. has still to consider such a commitment (Feldman, 2010).

In contrast to the overwhelming amount of research done in engineering and climate sciences, very little work has been done in the behavioral sciences to understand why people

would prefer to wait-and-see rather than act now (APA, 2009). Support for the wait-and-see approach may be influenced by the uncertainties in both the timing (e.g., how early in the future would we experience negative consequences due to climate change?) and the probability of occurrence of the future climate consequences (e.g., what is the likelihood of the future climate consequences?) (The Economist, 2010). These uncertainties are somewhat driven by the lack of consensus among climate experts on the probability and timing of future climate consequences (Nordhaus, 1994). For example, according to the IPCC (2007), the average sea level is expected to rise by 18–59 cm in 2090–2099 relative to 1980–1999; however, more recent estimates indicate an accelerated melting of ice and a range between 50 and 140 cm in the same time period (Rahmstorf, 2008). Given all the uncertainties, people may prefer to take a risky approach, i.e., wait-and-see rather than act now on climate mitigation.

According to Nordhaus (1994), people’s support for the wait-and-see approach may also be due to their lack of “experience and exposure” to the negative consequences of the earth’s climate. Recent research has suggested that human experience can often be a double-edged sword: Whether experience increases or decreases the wait-and-see approach may be determined by the nature of an individual’s experience. In a simulation-based laboratory experiment, Dutt and Gonzalez (2010) provided participants with realistic and negative experiences of future accumulation of CO<sub>2</sub> concentration. Participants were asked to control the CO<sub>2</sub> concentration in the atmosphere in a simulation called the “dynamic climate change simulation” (DCCS). Participants that were exposed to DCCS showed a lower proportion of wait-and-see choices in a follow-up task, compared to participants without experiences in the DCCS. Thus, an immediate and certain experience of CO<sub>2</sub> concentrations and the difficulties associated with its stabilization in the DCCS reduced the proportion of wait-and-see choices compared to no experience at all.

Unlike the exposure to immediate and certain experiences in a laboratory-based simulation, however, experiences of climate change in the real world are much delayed and uncertain, and exposure to realistic climate consequences can vary considerably from individual to individual. Thus, day-to-day personal experiences do not always agree with the scientific descriptions and predictions of future climate consequences: when there is two feet of snow on the ground, a person perceives the threat of climate change as far-off. For example, the recent “snowmageddon” in Washington, DC was sufficient enough for several congressmen to set back progress on an energy and climate bill pending legislation in Congress (Condon, 2010). Furthermore, given the uncertainties and complexity of the earth’s climate, people seem to rely more on their recent day-to-day experiences, rather than on the scientific predictions and written descriptions about the catastrophic consequences of climate change in the future. This behavior is supported by recent findings suggesting that as the complexity of a problem increases, people rely more on their own experience rather than on a written description of a risky situation (Lejarraga, 2010).

Motivated by the above observations, this research aims at understanding human decisions to “wait-and-see” or “act-now” when they are asked to experience different probabilities and timings of future climate consequences compared to when they are presented with a written description of the same. In this study, in a laboratory experiment, people make wait-and-see (risk-taking) or act-now (risk-averse) choices based on an experience or based on a written description of the future consequences of climate change. The experiment is a direct application of established Judgment and Decision Making (JDM) principles to the problem of wait-and-see on climate, and an extension of those findings that bring together the effects of the probability and timing of consequences on decisions from description and experience.

In the past, literature in JDM has either considered the influence of probability that is presented as a description or experience on people's decisions without considering the timing of consequences (Hertwig, Barron, Weber, & Erev, 2004; Kahneman & Tversky, 1979), or it has considered the influence of the timing of consequences as a description or experience on people's decisions without considering the probability (Loewenstein & Elster, 1992; Madden, Begotka, Raiff, & Kastern, 2003; Thaler, 1981). Thus, the contribution of this paper to JDM is unique and the climate problem is ideally suited for investigating the joint effects of probability and timing on people's decisions, as the future climate consequences are both delayed in time and are uncertain.

In what follows, we first summarize the JDM research relevant to generating our hypotheses about human behavior when making decisions from an experience or from a written description in situations that vary in the probability and timing of future climate consequences. Next, we present a laboratory experiment that manipulates the presentation of probability and timing in the form of an experience or a written description. Then, we present the results of this experiment and discuss the implications of the results to policy and JDM research.

### **7.3 Decisions from Description and Experience: Effects of Probability and Timing**

Current research in JDM has documented the differences in human risk-taking behavior when making decisions from experience or decisions from description (e.g., Hertwig et al., 2004; Hertwig, in press). In decisions from description, people are asked to choose between two alternatives described by their consequences and probabilities. In contrast, in decisions from experience, people make repeated decisions by clicking on two unlabeled buttons (representing

two alternatives) (Barron & Erev, 2003), or sample the consequences as many times as they wish before making a final choice for one of the two alternatives (Hertwig et al., 2004).

The main finding from this literature is that when making decisions from experience, people behave as if the low probability consequences have less impact than they deserve according to their objective probabilities, whereas in decisions from description people behave as if the low probability consequences have more impact than they deserve (consistent with the predictions from cumulative prospect theory) (Hau, Pleskac, Kiefer, & Hertwig, 2008; Hertwig, in press; Hertwig & Erev, 2009; Hertwig et al., 2004; Weber, Shafir, & Blais, 2004). As a result, the risk-taking behavior predicted by prospect theory in decisions from description gets reversed in decisions from experience. The reversal of people's risk-taking behavior has been attributed to the reliance on small samples in decisions from experience (Gottlieb, Weiss, & Chapman, 2007; Hertwig et al., 2004; Rakow, Demes, & Newell, 2008; Ungemach, Chater, & Stewart, 2009); differential impact of low and high probability consequences in gamble problems (Hau et al., 2008); and reliance on observed recent and frequent experiences of consequences (Gonzalez & Dutt, 2010; Hertwig, in press; Lejarraga, Dutt, & Gonzalez, in press; Weber et al., 2004).

The change in people's risk preferences documented in decisions from experience and description is highly relevant to our understanding of people's support for the wait-and-see approach for climate. As explained above, a written description of the probability and the timing of future climate consequences do not always agree with a person's day-to-day experiences of climate consequences. Currently, climate change might be perceived as a low probability event because the consequences are delayed and there is considerable individual variability of human experiences. For example, a consequence of climate change is a reduction of glaciers in the Himalayas, but the reduction happens slowly and most people living in cities do not experience

it. Thus, people might perceive future climate consequences as low probability events that have a negligible chance of occurring in the future. According to the JDM literature, we expect people to behave as if future climate consequences have less impact than they deserve according to their objective probabilities, when making decisions from experience. Similarly, we expect people to behave as if the future climate consequences have more impact than they deserve according to their objective probabilities, when making decisions from a written description. Thus, we hypothesize that:

**H1:** The proportion of wait-and-see choices will be greater when decisions are made from experience than from a written description.

Literature in JDM has also documented people's risk-taking choices to be a function of both the probability of a consequence (low probability or high probability) and of the sign of the consequence (loss consequence or gain consequence) (Kahneman & Tversky, 1979; Tversky & Fox, 1995; Tversky & Kahneman, 1992). The basic finding is a "fourfold pattern" (Hertwig, in press): In decisions from description, people are risk-taking when the probability of a loss is high and when the probability of a gain is low. Similarly, people are risk averse when the probability of a gain is high and when the probability of a loss is low (Tversky & Fox, 1995). This fourfold pattern of risk-taking and risk-aversion in decisions from description has been replicated in many studies in the past (Cohen, Jaffray, & Said, 1987; Fishburn & Kochenberger, 1979; Hershey & Schoemaker, 1980; Kahneman & Tversky, 1979). The fourfold pattern has been explained as per the tenets of prospect theory (Kahneman & Tversky, 1979), which suggests that the utility of a gamble problem is the product of a value function with a probability-weighting function. The shape of the value function is concave for gains and convex for losses, relative to a common reference point. In addition, the shape of the probability-weighting function is nonlinear such

that low probability consequences have more impact than they deserve according to their objective probabilities and moderate and high probability consequences have less impact than they deserve according to their objective probabilities.

In decisions from experience, researchers have shown a reversal of the fourfold pattern observed in decisions from description (Hertwig et al., 2004): People are risk-taking when the probability of a gain is high, but risk-averse when it is low. At the same time, they are risk-taking when the probability of a loss is low, but risk-averse when it is high (Hertwig, in press). Although it might become difficult to explain people's risk-taking behavior in decisions from experience according to the prospect theory in a form that theory was originally proposed (Kahneman & Tversky, 1979), researchers have tried to apply the prospect theory to decisions from experience by recalibrating the theory's parameters (Hau et al., 2008). Thus, the recalibrated weighting and value functions in the prospect theory are able to account for the observations in decisions from experience (in fact the recalibration makes the theory provide one of the best accounts for results in decisions from experience). However, the recalibrated parameters in decisions from experience also turn the weighting function into an identity function of probability and this questions whether the essence of the theory is retained, post recalibration (Hau et al., 2008; Hertwig, in press).

An act-now approach to climate change requires paying a cost (e.g., a carbon-tax), and thus, an act-now approach demands a monetary loss right now. In contrast, a wait-and-see approach to climate change, with some probability of occurring in the future, might entail losing a larger sum of money (e.g., as a tax). Given the inverse predictions of risk-taking behavior in decisions from description and experience, we expect that in description, people would prefer to wait-and-see (i.e., behave risk-taking) when they are presented with a carbon-tax payment that

has a high probability of occurrence in the future, but people would prefer to act-now (i.e., behave risk-averse) when they are presented with a tax payment that has a low future probability of occurrence. In contrast, in experience, people would prefer to wait-and-see when they experience a carbon-tax payment that has a low probability of occurrence in the future, but would prefer to act-now when they experience one that has a high probability of occurrence in the future. Thus, the proportion of wait-and-see choices should be greater when the probability of tax payment is low and should be smaller when the probability of tax payment is high. Therefore, in experience, the difference in the proportion of wait-and-see choices between a low and a high probability tax payment will be amplified compared to description. In description, the difference in the proportion of wait-and-see choices between a low and high probability tax payment will be attenuated.

We hypothesize that:

**H2:** The difference in the proportion of wait-and-see choices between a low probability and a high probability climate consequence will be greater when making decision from experience than when making decision from description.

In addition to the uncertainty in the occurrence of future climate consequences, there is also an uncertainty and lack of consensus on the timing of the consequences (e.g., how soon from now the climate consequences are expected to appear) (Nordhaus, 1994). As mentioned above, the decisions from experience and description paradigms in JDM have been used to assess the effects of the probability and timing of future consequences independently; the paradigms have still not been used to assess the joint effects of the probability and timing on people's risk preferences. According to the literature in time preferences, a person tends to avoid a high and certain cost now (e.g., defer an increase in tax) when the associated benefits are

distant in the future (magnitude effect) (Ainslie, 1975; Loewenstein & Elster, 1992; Thaler, 1981; Weber, 2006). However, a wait-and-see decision in the climate problem may also be influenced by the “discount rate” (the interest rate used to determine the present value of future tax payments) (dynamic-inconsistency effect) (Benzion, Rapoport, & Yagil, 1989). Due to the magnitude and dynamic-inconsistency effects, a person’s discount rate falls with an increase in time to pay a tax amount and an increase in magnitude of the tax amount.

The carbon-tax one would have to pay to mitigate climate change is predicted to grow as one decides to follow a wait-and-see approach (Stern, 2006). The nature of growth of the carbon-tax is nonlinear with small increments in the carbon-tax early in the future and larger increments late in the future (Stern, 2006). Thus, we expect that someone would prefer to pay a smaller carbon-tax now, rather than to pay a very large carbon-tax late in the future. Because of the nonlinear increase in the carbon-tax with increase in time, the tax one would need to pay early in the future (e.g., 10 years from now) might not be much larger than the carbon-tax one would need to pay right now. Therefore, one might decide to wait and pay the tax later in the future (wait-and-see) rather than pay it right now (act-now).

Previous research has tested the effects of providing a time delayed monetary reward on people’s time-preferences when the reward was presented either as a hypothetical reward (a written description of a delay in getting a reward) or as a real reward (an actual experience of the delay in getting a reward) (Madden et al., 2003). In their study, half of the participants were tested first with hypothetical rewards and then with real rewards; the other half were tested first with real rewards and then with the hypothetical rewards. In all cases, the amount of reward that could be won was \$10, which was offered to a participant at different time delays. Participants were asked to choose one of the two alternatives: “\$X delivered today and \$10 delivered in Y

years.” The \$X corresponded to an immediate reward and \$10 corresponded to a delayed reward. For the hypothetical rewards, participants did not receive any of the rewards that they chose in different problems. In contrast, for the real rewards, the reward was physically delayed and mailed out to participants after a time delay (Y), if participants had selected to delay the reception of the reward in a randomly selected problem. According to Madden et al. (2003) there was no difference in the amount of reward for which a participant switched from an immediate reward to a delayed reward between the real and hypothetical rewards. Madden et al.’s (2003) intervention of a real time delay corresponds to a situation in which people are exposed to the timing as an experience, while the hypothetical time delayed rewards corresponds to a descriptive situation in which people read a written description on how long they would need to wait for the reward.

Although Madden et al.’s (2003) study is about monetary rewards rather than monetary losses as in the current study, we believe that Madden et al.’s (2003) study gives some evidence that time preferences in description and experience would be similar. According to this and the literature in time preferences, we hypothesize that:

**H3:** The proportion of wait-and-see choices will be greater when climate consequences are expected to occur early rather than late in the future, and this effect will be the same whether the time is experienced or described.

## **7.4 Experiment**

We conducted a laboratory experiment to test participants’ wait-and-see or act-now choices in a climate problem where they had to make decisions based on a written description or from an experience, and under different conditions of the probability and timing of climate consequences.

## 7.4.1 Method

### 7.4.1.1 Experimental design

Participants were randomly assigned to one of two conditions: *description* and *experience*. In the *description* condition, participants read a written description of climate consequences, probabilities, and timing of the occurrence of consequences in two different alternatives, and were asked to choose one of the alternatives based on the description (N = 51). Thus, the consequences, probability, and timing were explicitly given in a written form to the participants. In the *experience* condition, participants sampled two different alternatives presented as unlabeled buttons as many times as they wanted to, and were then asked to finally choose one of the two alternatives (N = 50). The probability and timing of climate consequences were not explicitly provided, but they were determined by participants based upon their sampling. In both conditions, one alternative reflected the wait-and-see (risk-taking) approach and the other alternative, the act-now (risk-averse) approach.

Each participant received four problems in a random order, where the wait-and-see alternative differed according to the probability and timing of the climate consequences: a low probability consequence early (p=0.05 and n=10 years from now); a low probability consequence late (p=0.05 and n=100 years from now); a high probability consequence early (p=0.95 and n=10 years from now); and, a high probability consequence late (p=0.05 and n=100 years from now). Each alternative presented consequences as a monetary outcome, which was derived in terms of a carbon-tax.<sup>25</sup> The carbon-tax was determined by using a popular *Stern Review* proposal for mitigating future climate change (Stern, 2006). The Stern Review proposal was run in the

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<sup>25</sup> The carbon-tax takes into account both the cost of damages due to future climate change as well as its cost of abatement.

Dynamic Integrated Climate Economy model (Nordhaus, 2008) with the Stern assumption of a 1.4% discount-rate.<sup>26</sup> The model gave a carbon-tax of \$1,400 per-person-per-year for the act-now alternative. Furthermore, for the wait-and-see alternative, the model run gave a carbon-tax of \$18,000 per-person-per-year for 10 years in the future from now and \$340,000 per-person-per-year for 100 years in the future from now. These carbon-taxes were used as the outcomes in all problems in different conditions.

#### **7.4.1.2 The description condition**

The four problems used in the description condition are shown in Figure 7-1. The wait-and-see and act-now alternatives were randomly assigned to be shown on the right or left of the computer screen. A participant read and chose one of the two alternatives in each of the four problems, presented one-by-one in random order. In the act-now alternative, a person had to pay a one-time carbon-tax of \$1,400 now for sure. In contrast, in the wait-and-see alternative,  $Y$  years from now ( $=10$  in the early case or  $=100$  in late case), a person had to pay a one-time carbon-tax of  $\$X$  ( $=\$18,000$  in the early case or  $\$340,000$  in the late case) with a probability  $P$  ( $=.05$  for low or  $=.95$  for high), or  $\$0$  otherwise.

#### **7.4.1.3 The experience condition**

In the experience condition, a participant clicked one of two unlabeled buttons (Figure 7-2). Each button corresponded to one of the two alternatives, act-now or wait-and-see. Clicking on one of the buttons gave a participant a carbon-tax ( $= \$1,400$ , if the button assigned to the act-now alternative was chosen). Clicking on the other button gave the participant another carbon-

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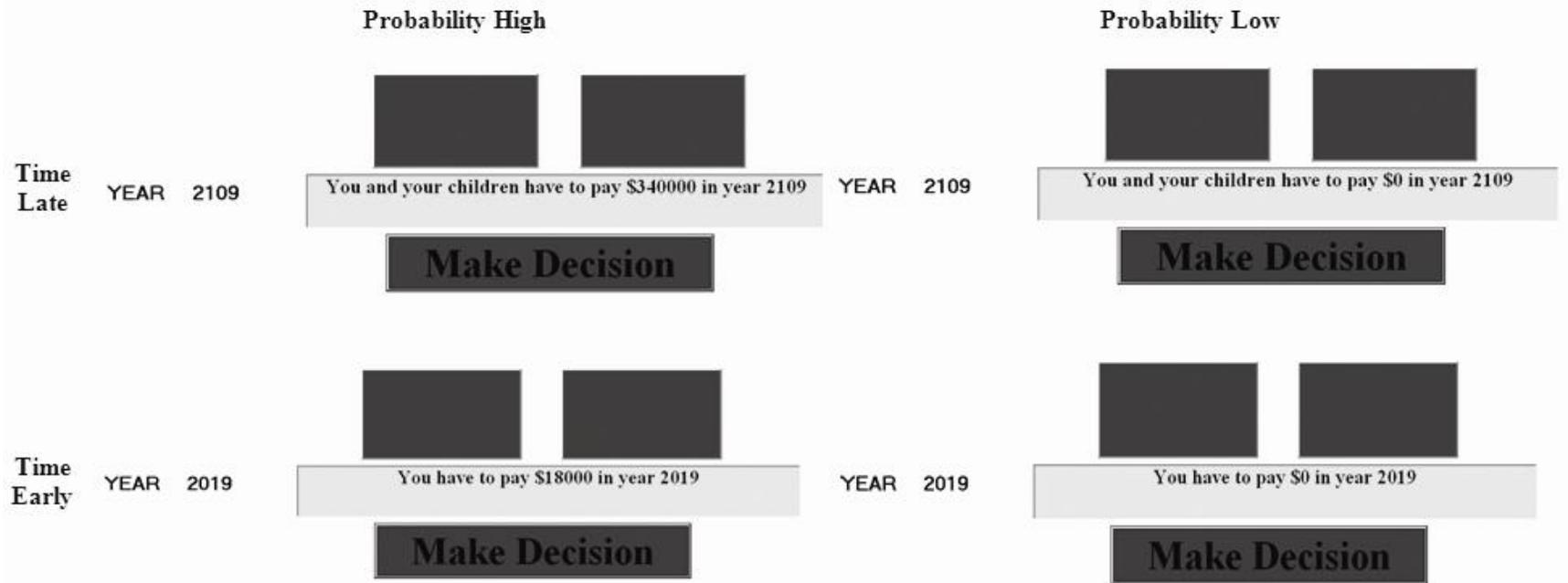
<sup>26</sup> The output from the DICE model run contained a carbon-tax in units of dollar per ton of carbon. Thus, for generating the dollar per-person-per-year carbon-tax, an average of 5 tons of carbon consumption per-person-per-year was assumed. Furthermore, the carbon-tax in units of dollar per ton of carbon was multiplied by 5 tons of carbon consumption per-person-per-year.

tax (\$X and \$0). The value of \$X could be either \$18,000 in the early case, or \$340,000 in the late case, in the four problems.



Figure 7-1. The four problems presented to each participant in the description condition.

Furthermore, clicking the wait-and-see alternative delayed the presentation of the carbon-tax by a certain number of years, depending on the timing ( $Y=10$  years in the early case or  $Y=100$  years in the late case). One year corresponded to a one-second of real time-delay. The one-second to one-year correspondence is motivated by previous time preference studies with monkeys where a similar magnitude of delay had been used (McClure, Ericson, Laibson, Loewenstein, & Cohen, 2007). Participants were first encouraged to sample both button options as many times as they wanted to, to gain experience in a problem. Sampling essentially meant clicking on one of the two buttons to find out the carbon-tax that a participant would have to pay and to experience the corresponding time delay. A participant was asked to make a final choice by clicking the “Make Decision” button after he was satisfied with his sampling. Although sampling the alternatives in a problem did not cost the participants money, it involved different time costs depending on the timing (early, late).



**Figure 7-2. The four problems presented to each participant in the experience condition. The two choice alternatives in each problem were presented as two blank buttons that could be sampled many times by clicking in the buttons. Once a participant had sampled both buttons many times, a final decision could be made by clicking the “Make Decision” button followed by the button the participant wanted to choose.**

To test H1, we compared the proportion of wait-and-see choices across the experience and description conditions. To test H2, we compared the difference between the proportion of wait-and-see choices in the low probability problems ( $p=0.05$ ) and the proportion of wait-and-see choices in the high probability problems ( $p=0.95$ ) within the experience and description conditions, respectively. Finally, to test H3, we compared the proportion of wait-and-see choices between problems where the timing was early or late, within the experience and description conditions, respectively.

#### **7.4.1.4 Participants**

One hundred and one undergraduate and graduate students at Carnegie Mellon University participated in this experiment. Sixty-two percent of the participants were males. Ages ranged from 18 years to 57 years (Mean = 25, S.D. = 8). All participants started with \$7 and depending upon their final choice, they could lose money. Only a participant's final choice in both the experience and description conditions affected the final payment. Participants were told this fact in the instructions before the start of their experiment. The carbon-taxes could be \$1,400 in the act-now and \$0, \$18,000, or \$340,000 in the wait-and-see alternative. To pay participants, we scaled the actual carbon-taxes to smaller amounts. We used a log scaling to calculate a participant's earnings in the experiment. For example, if due to a participant's final decision in a problem, the carbon-tax generated was \$X, then the adjustment to the earnings was  $= -0.1 * \text{Log}_{10}(\$X + 1)$ . Thus, for a \$1,400 tax, a participant lost ¢31. Similarly, for an \$18,000 or a \$340,000 tax, a participant lost ¢43 and ¢55, respectively. The log scaling ensured that none of the participants lost an amount greater than \$2 in total depending upon the final carbon-tax they would have to pay in each problem. Also, the use of the log scaling ensured that the effect of differences in the magnitudes of \$1,400, \$18,000, and \$340,000 was similar in the final payment

that a participant received. The log scaling was not revealed to participants, but they were told that they might lose up to \$2 depending upon their final decisions in the problems.

#### **7.4.1.5 Procedure**

Participants read the instructions that appeared on a computer terminal. The experimenter answered any questions before the participant could begin the experiment. As part of the instructions, participants were told to assume that “they earn a compensation of \$55,000 in 2009” in each problem presented to them (this was the value for the average per-person-per-year salary projected for 2009 according to the year 2000 U.S. census).

#### **7.4.2 Results**

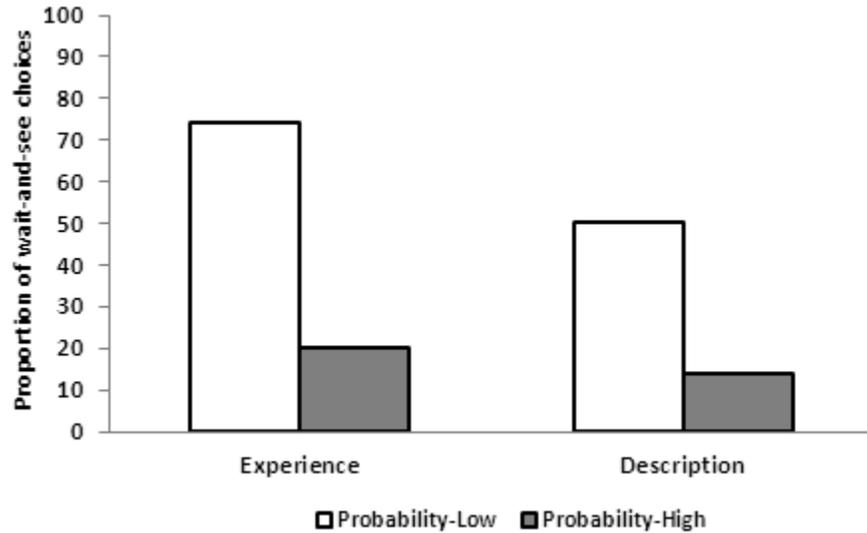
Across the four problems in the two conditions, experience and description, there was a significantly greater proportion of wait-and-see choices in the experience condition (47%) than in the description condition (33%),  $\chi^2(1) = 8.44, p < .01, r^{27} = .15$ . This result supports H1.

Figure 7-3 presents the proportion of wait-and-see choices in the experience and description conditions according to the probability of the occurrence of consequences (low or high). In experience, there was a significant difference in the proportion of wait-and-see choices when the probability was low (74%) compared to when the probability was high (20%),  $\chi^2(1) = 58.53, p < .001, r = .54$ . Similarly, in description, there was a significant difference in the proportion of wait-and-see choices when the probability was low (50%) than when the probability was high (14%),  $\chi^2(1) = 29.45, p < .001, r = .38$ . Furthermore, in support of our expectation in H2, the difference in the proportion of wait-and-see choices between the low and high probability (54%) in the experience condition is greater than the difference in the proportion

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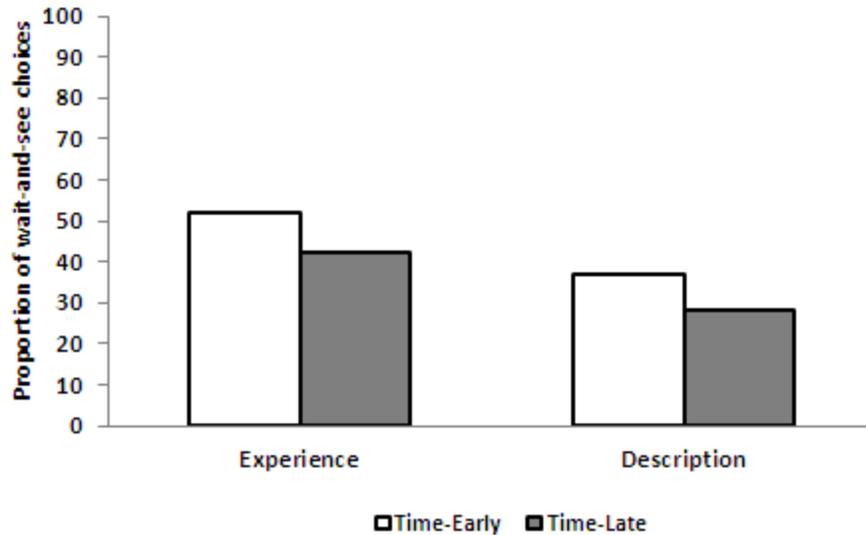
<sup>27</sup> The  $r$  refers to the effect-size unless otherwise indicated.

of wait-and-see choices between the low and high probability (36%) in the description condition ( $r_{\text{experience}} (= .54) > r_{\text{description}} (= .38)$ ).



**Figure 7-3. The proportion of final wait-and-see choices in the experience and description conditions according to the probability of occurrence of future climate consequences (low or high).**

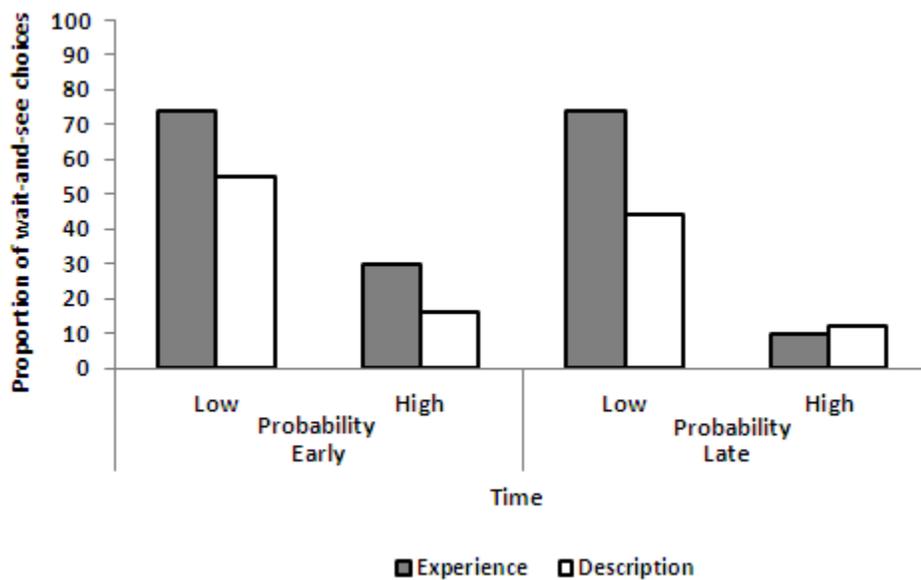
Figure 7-4 presents the proportion of wait-and-see choices in the experience and description conditions according to the timing of the climate consequences (early or late). In experience, the difference in the proportion of wait-and-see choices when the timing of consequences was early (52%) than late (42%) was not significant,  $\chi^2(1) = 2.01, ns, r = .10$ . Similarly, in description, the difference in the proportion of wait-and-see choices when the timing of consequences was early (37%) than late (28%) was not significant,  $\chi^2(1) = 1.81, ns, r = .09$ . Thus, H3 is not supported.



**Figure 7-4. The proportion of final wait-and-see choices in the experience and description conditions according to the timing of the climate consequences (early or late).**

Although we did not have a prediction for the interaction between the timing and probability of future climate consequences, we present the combined effects of probability and timing in Figure 7-5. This figure shows the proportion of wait-and-see choices for each of the four problems used in our experiment. The proportion of wait-and-see choices was greater in experience than in description conditions in all cases except for these two: when the probability of the consequence was high and the time was late and when the probability of consequence was high and the time was early. When the probability of the consequence was high and the time was late, there were 10% wait-and-see choices in experience and 12% wait-and-see choices in description ( $\chi^2(1) = 0.13, ns, r = .04$ ). Similarly, when the probability of the consequence was high and the time was early, there were 30% wait-and-see choices in experience and 16% wait-and-see choices in description ( $\chi^2(1) = 2.59, ns, r = .16$ ). However, when the probability of the consequence was low and the time was early, the proportion of wait-and-see choices was significantly greater in the experience condition (74%) than in the description condition (55%),

$\chi^2(1) = 3.99, p < .05, r = .19$ . Similarly, when the probability of the consequence was low and the time was late, the proportion of wait-and-see choices was significantly greater in the experience (74%) than the description (44%) condition,  $\chi^2(1) = 9.30, p < .01, r = .31$ . These results suggest that the wait-and-see choices were directly affected by the low probability of the consequences and not by the time. When the probability of the climate consequences is high, there is a smaller proportion of wait-and-see choices regardless of the time.



**Figure 7-5. The proportion of final wait-and-see choices in the experience and description conditions as a function of the time (early or late) and the probability (low or high) of the occurrence of climate consequences.**

#### 7.4.2.1 Sampling in experience

Across all four cases in the experience condition, participants sampled both alternatives less than 5 times on average (thus, the sample size was very small). The median number of samples of the act-now alternative was: 2 for late-and-high case, 1 for late-and-low case, 1 for early-and-high case, and 1 for early-and-low case. Similarly, the median number of samples of the wait-and-see alternative was: 1 for late-and-high case, 1 for late-and-low case, 1 for early-

and-high case, and 2 for early-and-low case. Although the timing of the climate consequences did not affect the proportion of wait-and-see choices (see results above), the timing did affect the sampling of the wait-and-see alternative (the effect of the timing on the act-now alternative was absent with  $z = -0.60$ ,  $p = .55$ , and  $r = .04$ ). Remember, the timing was only manipulated in the wait-and-see alternative and not in the act-now alternative. The number of samples in the wait-and-see alternative for an early timing of consequence (mean = 1.76) was significantly greater than the number of samples of the wait-and-see alternative for a late timing (mean = 1.39) with  $z = -2.31$ ,  $p = .02$ , and  $r = .16$ . Furthermore, there was an effect of the probability of the future climate consequences on the number of samples in the act-now alternative (the effect of the probability of the climate consequences on the number of samples of the wait-and-see alternative was absent with  $z = -1.48$ ,  $p = .14$ , and  $r = .10$ ). The number of samples in the act-now alternative for a high probability of consequence (mean = 1.95) was significantly greater than the number of samples of the act-now alternative for the low probability (mean = 1.32) with  $z = -3.14$ ,  $p < .01$ , and  $r = .22$ . Thus, it was as if a participant who encountered the high probability consequence on the wait-and-see alternative, also wanted to check the consequence in the act-now alternative more often than the wait-and-see alternative before making his final choice.

The small sample size in different cases, on account of the probability and the timing of the consequence, made participants observe the low probability consequence at less than its expected probability. Table 7-1 provides the proportion of wait-and-see choices in different cases as a function of the frequency of observing a low probability consequence as being less than or more than or equal to its expected value. The expected value is determined by the product of “n,” the number of samples of the wait-and-see alternative performed by a participant in a case, and “p,” the true probability of observing a low probability consequence in the case. The table shows

these percentages for different problem cases, where the monetary consequences, the probability of the non-zero wait-and-see consequence, and the low probability of the wait-and-see consequence are clearly labeled. When the probability of the consequence was low, there was a clear evidence of people behaving as if the low probability consequence had less impact than it deserved according to its objective probability (irrespective of the timing): The proportion of wait-and-see choices, where the low probability was encountered less frequently than expected, was greater than the proportion of wait-and-see choice, where the low probability was encountered as or more frequently than expected (78% >> 40% and 81% >> 29%). However, the proportion of wait-and-see choices, where the high probability was encountered less frequently than expected, was not consistently greater than the proportion of wait-and-see choices, where the high probability was encountered as or more frequently than expected (32% > 17% and 8% < 100%). This observation is an explanation for a significantly greater proportion of wait-and-see choices in the experience condition when the probability was low, and a significantly smaller proportion of wait-and-see choices in the experience condition when the probability was high (see Figure 7-5).

**Table 7-1. The proportion of wait-and-see choices with a low probability consequence as a function of the frequency of occurrence of the low probability consequence.**

Cases		Problems			Proportion of wait-and-see choice (with low probability consequences)	
N	P	Wait-and-see Choice	Act-now Choice	Low Probability Consequence	# < np <sup>1</sup> %	# ≥ np <sup>2</sup> %
Early	Low	18,000; 0.05	1,400; 1.0	18,000; 0.05	78 (35/45) <sup>3</sup>	40 (02/05)
Early	High	18,000; 0.95	1,400; 1.0	0; 0.05	32 (14/44)	17 (01/06)
Late	Low	340,000; 0.05	1,400; 1.0	340,000; 0.05	81 (35/43)	29 (02/07)
Late	High	340,000; 0.95	1,400; 1.0	0; 0.05	08 (04/49)	100 (01/01)

Note. <sup>1</sup> Proportion of wait-and-see choice with a low probability consequence, where the low probability consequence was encountered less frequently than expected, i.e.,  $n \cdot p$ , where  $n$  is the number of samples of the wait-and-see choice performed by a participant and  $p$  is the probability of the occurrence of the low probability consequence. <sup>2</sup> Proportion of wait-and-see choice with a low probability consequence, where the low probability consequence was encountered as or more frequently than expected. <sup>3</sup> Numbers in brackets refer to the actual frequencies of different proportions.

## 7.5 Discussion

This research contributes to a better understanding of people’s decisions to wait-and-see rather than act-now in a climate problem. We demonstrate that people’s support to delay actions to mitigate climate change is largely influenced by the probability of the occurrence of future climate consequences and not by the timing of those occurrences. Further, the decision to choose wait-and-see is influenced by people’s experience and exposure to the probability of climate consequences, regardless of its timing.

In general, we find a greater proportion of wait-and-see choices when decisions are made from experience rather than from a written description (H1). In a related research, Dutt and Gonzalez (2010) found that when people are exposed to certain negative experiences and realistic consequences of climate change in a simulation, they reduced the proportion of wait-and-see decisions in a follow-up judgment task compared to participants without the experience in the simulation. The experience gained in the simulation was immediate and certain, because participants were given a constant CO<sub>2</sub> goal value to maintain by manipulating their yearly CO<sub>2</sub> emissions and absorptions. In contrast, in this study, participants were exposed to future climate consequences that were both probabilistic and uncertain in the timing of their occurrence. Thus, a participant might have to either pay a carbon-tax sometime in the future or no tax at all, where the tax magnitude and time delay were determined by the underlying probability and timing of the consequences. Therefore, results in this study agree with the observations of Dutt and Gonzalez (2010), that experience is a double-edged sword: A certain and more immediate experience reduces people's wait-and-see choices, whereas an uncertain and delayed experience increases their wait-and-see choices for climate.

This research also extends the main findings on decisions from experience and description by analyzing the combined effects of probability and time together. We find that the difference in wait-and-see choices between the low probability and high probability consequences is significantly greater when participants experience the climate consequences than when participants read about the low and high probability climate consequences as a written description (H2).

While making decisions from experience, people behave as if the low probability consequences have less impact than they deserve, according to its objective probabilities, and

the high probability consequences have more impact than they deserve, according to their objective probabilities (see Table 7-1). In contrast, while making decisions from description, people behave as if the high probability consequences have less impact than they deserve, according to its objective probabilities, and the low probability consequences have more impact than they deserve, according to their objective probabilities. This result of less impact of the low probability consequences in experience may be explained further by the known small-sampling effect (Hertwig et al., 2004). In experience, when the probability of a consequence is low, people encounter that low probability consequence less frequently than expected due to their small sampling of the two alternatives, as was found in our results (also see Table 7-1).

However, when the probabilities and consequences are described rather than experienced, the difference between the low and high probability events is smaller than that in experience. This finding is consistent with the predictions of prospect theory (Kahneman & Tversky, 1979). According to prospect theory, in decisions from description, people behave as if a low probability consequence has more impact than it deserves, according to its objective probability, and a high probability consequence has less impact than it deserves, according to its objective probability. Although in our results, the predictions from prospect theory explain the reduction in the difference in the proportion of wait-and-see choices in description between the low probability and high probability, the difference does not disappear. Thus, we still find that a significantly greater proportion of people choosing to wait-and-see for the low probability than the high probability in description. One possible reason for this observation could be that the carbon-tax amounts used in the study are different and significantly greater than those that have been used in past studies (Hau, Pleskac, Kiefer, & Hertwig, 2008; Hertwig, in press; Hertwig et

al., 2004; Herwig & Erev, 2009; Kahneman & Tversky, 1979; Weber, Shafir, & Blais, 2004) that have documented the results of people's risk preferences in decisions from description.

Furthermore, we find there was no significant difference in the proportion of wait-and-see choices between times that were early or late, when participants experienced or read descriptions of carbon-tax consequences. This finding is the most surprising and unexpected given that people would tend to adopt a wait-and-see approach because the detrimental consequences are expected to happen in the distant future and not in the present. One explanation is that the timing is observed by people in the study as something that creates a wait and thus a cost. However, in the real world, the time delay might not necessarily be perceived as a cost (because when people decide to wait in the real world, they might spend that waiting time in more productive activities). The support for this observation comes from the fact that the time, early and late, did influence the number of samples people made of the wait-and-see alternative (on account of the late time being perceived by people as costly). However, another explanation for the lack of difference could also be that the early and late times were not salient enough in the study. The lack of saliency could be due to an enormously scaled-down version of the "real experience," where one year corresponded to a one-second of real-time delay in experience and no time delay in description. Although there was no difference in the proportion of wait-and-see choices between times that were early or late, our findings do support those by Madden et al. (2003), who found that although there were significant differences in choices for delayed and immediate rewards (unlike us); the direction of the difference was the same when the time was either experienced or described. We plan to do follow up studies to test the effects of early and late time after we have taken into account the above listed factors that could potentially be reasons for the lack of difference.

In the past, the JDM literature has documented the individual effects of the probability and timing of consequences on people's risk- and time- preferences, respectively. However, we know little about how choices are influenced by the experience and description of both the timing and the probability of the consequences. Our findings indicate that people's wait-and-see choices for climate are influenced primarily by their perception of the probability of climate consequences. Thus, a person's choice to wait-and-see is governed by a low or high probability of future climate consequence. A low probability has a moderating effect in the presentation of high taxes in the case of an early or late timing of a consequence: an early or late time makes the magnitude of carbon-tax high; however, a low probability makes a high tax-consequence rare. This explanation is confirmed by the fact that the difference in the proportion of wait-and-see choices disappeared when an early or late timing of climate consequence incurred a large tax that occurred with a high probability, in which case, very few people chose the wait-and-see alternative.

We presented people with consequences of future climate change as carbon taxes. This is, of course, legitimate and also makes experimentation easier as different alternatives can easily be compared by participants. However, we believe that there are other ways of simulating people's imagination and giving people experiences of climate consequences that are different from tax payments. For example, in the past, Dutt & Gonzalez (2011) have given participants experiences of climate change by showing them the effects of the CO<sub>2</sub> emissions on the CO<sub>2</sub> concentration levels. Furthermore, Dutt and Gonzalez (2011) associated the increases in the CO<sub>2</sub> concentration levels above a pre-define goal with a corresponding increase in temperature and sea level rise in the world. Similarly, some other means of providing climate experiences could be in the form of pictures of objects that participants associate with (e.g., a house one would live-in, which is close

to a sea coast), and how those objects might be affected by climate change (e.g., severe waves and winds due to future climate change).

Finally, one might argue that it is possible that the likelihood of climate change is currently high, but the probability that specific intervention and/or research programs are cost effective, is low. It is to be noted that the carbon tax consequences that people faced in different problems in the study included both costs of damages due to future climate change as well as *costs of abatement* of climate change (the latter cost forms a part of the cost of different interventions). Thus, another possible explanation of a greater wait-and-see in experience compared to description could be that our experience with climate interventions can reduce our tendency to invest in addressing climate change because these interventions are perceived as costly. Also, as observed in our results, one might show more support for the wait-and-see alternative after costly experiences of an intervention. However, one should also acknowledge that currently we do not know whether the probability associated with future climate change, or whether the probability of the cost-effectiveness of its interventions *in the future* will be low or high. Thus, in the study, we assumed both possibilities, i.e., when the probability is *low* in the future and when the probability is *high* in the future. Although in the study, we provided tax consequences that were detached from a particular climate intervention, it will be interesting to test whether the experience of one of the intervention programs (e.g., switching off lights in one's home for 1 hour in the evening) could reduce our tendency to invest in addressing the climate change issue due to it being costly and due to the probability of the intervention's cost-effectiveness being low currently, and it being low or high in the future.

## **7.6 Contributions of the Study to Judgment and Decision Making**

Unlike previous studies on decisions from experience and description, where only the probability of the risky outcomes was manipulated, we manipulate both the probability and timing in a problem involving a binary-choice in conditions of experience and description in this study. This unique manipulation allows us to experiment with a practical problem with distinctive characteristics like climate, where the consequences are both probabilistic and delayed in time, and to measure how these factors interact together to influence people's wait-and-see choices. Although this study applied JDM principles to people's wait-and-see behavior on climate, similar applicative contributions of decisions from experience and description paradigms have been made in other practical problems. For example, Shafir, Reich, Tsur, Erev, and Lotem (2008) have demonstrated the certainty effect in descriptive-based and reversed-certainty effect in experience-based choice both for bumble bees as well as humans. Similarly, Yechiam, Barron, and Erev (2005) have demonstrated that the risk sensitivity of local Israeli residents differ from those of the international tourists on account of their personal experiences. Yechiam et al. (2005) have reported similar findings in a laboratory experiment involving a binary-choice problem.

We believe that the distinctive characteristics of the climate problem make it both interesting and challenging to apply the theories and methods of JDM research. Thus, unlike other problems, the climate problem is naturally suited to and allows us to test the joint effects of the probability and timing of consequences in a single problem on people's wait-and-see choices.

## **7.7 Implications of the Findings to Policy**

There is little scientific doubt that climate change will occur if we continue on a path of increasing greenhouse gas emissions (IPCC, 2007). According to Weber (2006), an act-now

approach could be adopted if the consequences due to climate change could arouse visceral reactions of fear in the minds of the general public. One method for doing so is to provide climate consequences that are either descriptive or experiential. The descriptive information could appear using letters and numbers, whereas the experiential information could form a part of a figure or imagery (i.e., through commercials and movies like *An Inconvenient Truth* or *The Day After Tomorrow*) (Leiserowitz, 2004) or a dynamic simulation (Dutt & Gonzalez, 2010). Our results show that people like to act-now when they either experience or read a written description of climate consequences that communicates a high probability of climate consequences occurring in the future. Thus, based upon our results, one way to evoke visceral reactions of fear or a conscious awakening is to present people with descriptions and experiences of future climate consequences that make them perceive these consequences as occurring with a high probability in the future. In fact, Leiserowitz, (2004) found that a greater proportion of people who watched the movie, *The Day After Tomorrow*, wanted to act now on the climate problem than those who did not watch the movie. Future research that applies JDM principles on climate change would benefit by building upon the findings of this study.

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## **Chapter 8: Decisions from Description and Experience: Effects of Probability, Cost, and Timing of Climate Consequences**

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### **Effects of cost, timing, and probability of climate consequences in decisions from description and decisions from experience**

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## 8.1 Abstract

This study investigates how a description or experience of cost, timing, and probability of future climate consequences affects people's risky wait-and-see behavior for climate change. In a laboratory experiment, carbon-tax consequences were presented to participants in one of two forms: a written description, where the cost, timing, and probability were explicitly provided; or experience, where the cost, timing, and probability were sampled through unlabeled buttons. Eight problems, each with an act-now (safe) option and a wait-and-see (risky) option, were presented in description and experience such that the probability of consequences on the wait-and-see option was low or high, the timing was early or late, and the cost was small or large. Results indicate that while in both experience and description, the proportion of wait-and-see choices was greater when the probability was low rather than high, the difference between low and high probability was amplified in experience and attenuated in description. Also, the proportion of wait-and-see choices was greater when the timing was late than early, and when the cost was small than large; however, the effects of timing and cost were absent in experience. These results are explained by people's risk- and time- preferences, and the moderating effects of experience of climate consequences. We discuss the implications of our findings for risk communication in climate change.

*Keywords:* time, probability, cost, decisions from experience, decisions from description, climate change

## 8.2 Introduction

Unlike other global problems with risky outcomes (e.g., poverty, education, and war etc.), climate change is unique: It affects us all alike, and its future consequences might be costly, delayed, and uncertain (Sterman, 2008; Weber, 2006). Climate change is a serious problem needing immediate attention. The Intergovernmental Panel on Climate Change (IPCC) (2007), the Joint Science Academies (JSA) (2007), and the World Meteorological Organization (WMO) (2006) have jointly concluded that the current levels of greenhouse-gas emissions far exceed historic levels and that these emissions must be urgently and significantly reduced. Failing to do so, the world could face catastrophic consequences in the future.

Despite the widespread scientific evidence of the seriousness and urgency of the climate problem, a large number of people, including citizens, policymakers, and scientists, prefer to take risks and wait, rather than act now to reduce emissions, i.e., they exhibit a risk-seeking “wait-and-see” behavior for climate change (Dutt & Gonzalez, 2011, in press, 2010; Leiserowitz, 2007; Nordhaus, 1994; Sterman, 2008; Sterman & Booth Sweeney, 2002, 2007).

Amidst the wait-and-see behavior for climate change, economists and climate scientists seem to be in disagreement about the cost (how much?), timing (when?), and probability (with what chance?) of the impacts of future climate consequences (Nordhaus, 1994). For example, when economists and climate scientists from the National Academy of Sciences (NAS) were asked to assess the cost of damages in gross world product (GWP) for a rapid 6°C rise in average earth’s temperature by 2090, the estimates varied between 0.8% of GWP (for economists) and 62% of GWP (for climate scientists) (Nordhaus, 1994). Similarly, when asked to assess the probability of damages occurring under the same scenario, estimates varied between 0.3% (for economists) and 95% (for climate scientists). Moreover, the study admitted to being uncertain

about the timing of climate consequences and gave different scenarios to the NAS panel. For example, one scenario was projected more than 100 years from now in the year 2175, and another less than 100 years from now in the year 2090. Generally, the economists' predictions seem to *underweight* the cost and probability; whereas, the natural scientists' predictions seem to *overweight* the same cost and probability. According to Nordhaus (1994), the climate scientists' overweighting was due to their widespread exposure to *descriptive* models of climate change; whereas, economists' underweighting was driven by their widespread reliance on their current *experiences* of climate change in the absence of descriptive climate knowledge. In fact, recent research in judgment and decision making (JDM) has revealed that decisions made from a description (like those of climate scientists) overweight low probability consequences; whereas, decisions made from experience (like those of economists) underweight low probability consequences (Hertwig, Barron, Weber, & Erev, 2004).

In this paper, we test how decisions made from description or experience differ according to the cost, timing, and probability of climate consequences. The literature in JDM has documented the influence of underweighting and overweighting of low probability consequences on people's risk-seeking behavior in description and experience, respectively (Hertwig et al., 2004). However, there is not yet an empirical study that has evaluated the influence of descriptive and experiential probability of consequences in combination with their cost and timing on people's risk-seeking behavior.

### **8.3 Background and Hypotheses**

Literature in JDM has studied people's risk-seeking choices in decisions made from a written description or from experience (Hertwig, in press; Hertwig et al., 2004; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). In decisions from description, people are asked to

choose between two options in which all consequences and their probabilities are stated (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). In contrast, in decisions from experience, people are provided with two blank buttons (representing the two options) where they can first sample the consequences by clicking the buttons as many times as they wish (with no costs) before deciding which option to choose for real (Hertwig, in press; Hertwig et al., 2004).

People's risk-seeking choices in decisions from description and experience are a function of both the probability (low or high) and the sign of the consequence (loss or gain) (Kahneman & Tversky, 1979; Tversky & Fox, 1995; Tversky & Kahneman, 1992). The basic finding is a "fourfold pattern" (Hertwig, in press): In decisions from description, people are risk-seeking when the probability of a loss is high and when the probability of a gain is low, while people are risk-averse when the probability of a gain is high and when the probability of a loss is low (Tversky & Fox, 1995). This fourfold pattern in decisions from description has been replicated in many studies in the past (Cohen, Jaffray, & Said, 1987; Fishburn & Kochenberger, 1979; Hershey & Schoemaker, 1980; Kahneman & Tversky, 1979), and it has been explained by prospect theory (Kahneman & Tversky, 1979).

In contrast, a reversal of the fourfold pattern appears when people make decisions from experience (Hertwig, in press; Hertwig & Erev, 2009; Hertwig et al., 2004): People are risk-seeking when the probability of a gain is high, but risk-averse when it is low. At the same time, they are risk-seeking when the probability of a loss is low, but risk-averse when it is high (Hertwig, in press). Although people's behavior in decisions from experience may be difficult to explain according to the original parameters of prospect theory (Kahneman & Tversky, 1979), researchers have found that by recalibrating the theory's weighting and value function

parameters with human data, it is possible to account for risky choices in decisions from experience. However, the recalibration also turns the weighting function into an identity function of probability, which sheds light on the boundaries of prospect theory's applicability in its original form (Hau, Pleskac, Kiefer, & Hertwig, 2008; Hertwig, in press).

In previous research, we have presented an explanation of wait-and-see (risk-seeking) behavior for climate change when the information about probability and consequences was presented as a description or as experience (Dutt & Gonzalez, in press). We presented participants with choice problems as experience or as a written description with two options: act-now (risk-averse) and wait-and-see (risk-seeking). The act-now option entailed paying a cost (e.g., a carbon tax of certain magnitude) right now; whereas, the wait-and-see option entailed losing a larger cost (as a tax) compared to the act-now choice with some probability (low or high) in the future. It was found that the difference in proportion of wait-and-see choices between a low and high probability tax payment was amplified in experience; whereas this difference was attenuated in description. The amplification in experience was explained by the four-fold pattern: people prefer to wait-and-see when they experience a carbon tax (a loss) that has a low probability, but prefer to act-now when they experience one that has a high probability. Similarly, the reason for the attenuation of the difference in description is due to the exact opposite effects of low and high probability carbon taxes compared to those in experience. Thus, a first goal in the current paper is to replicate this result. For the wait-and-see choices for climate change we expect:

**H1:** The difference in the proportion of wait-and-see choices between a low probability and a high probability consequence will be greater when making decisions from experience than from description.

As mentioned earlier, there is currently uncertainty about when or how soon climate consequences are expected to appear (Nordhaus, 1994; Öncüler, 2010). We have also investigated the effects of timing of future cost consequences (as carbon taxes) on people's wait-and-see behavior (Dutt & Gonzalez, in press). In previous research, we manipulated the timing on the wait-and-see option such that for an early occurrence of climate consequences (10 years in the future), the associated cost was smaller compared to that for a late occurrence of climate consequences (100 years in the future) (the cost increased directly as a result of timing with a smaller cost for early timing and a larger cost for late timing). Results revealed that the proportion of wait-and-see choices was not influenced by timing, early or late, and it was similar in both experience and description. One reason for this result is that the time delay was perceived only as a cost; however, in reality people might be able to earn salaries and might reap incentives during the time they wait to act on climate change. For example, some policymakers think that wait-and-see behavior to climate mitigation actions *will enable* people and industry to reap greater economic benefits in the time they wait to act on climate change through interest on savings in banks (Schoof, 2011). Therefore, there is a possibility that the accrued incentives in waiting would balance out the costs of future climate consequences, especially if these consequences occur late in the future. Motivated by these arguments, we modified our previous paradigm by making the time delay costly but also beneficial.

According to literature on inter-temporal choice, people's repeated choices for risky and safe options in both experience and description under a time delay depend on whether the delay provides an incentive (Luhmann, Chun, Yi, Lee, & Wang, 2008; Wu, 1999). Therefore, people would prefer to choose a risky option which produced a time delay between repeated choices so long as they could derive an incentive during the waiting time.

For climate, if the consequences occur early in the future (e.g., 10 years from now), then the cost (carbon tax) of consequences may outweigh the gains that people make while waiting for a short time. However, if the climate consequences occur later in the future (e.g., 60 years from now), the economic gains people make while waiting may outweigh the cost (carbon tax). If people's time-preferences are driven by the option that provides them with a greater incentive in both experience and description (Dutt & Gonzalez, in press; Luhmann et al., 2008; Wu, 1999), then we expect a greater proportion of wait-and-see choices for later climate consequences than earlier consequences. We hypothesize that:

**H2:** The proportion of wait-and-see choices will be greater when consequences are expected to occur late rather than early in the future, and this effect should not differ whether the time is experienced or described.

Aside from the timing, there is also uncertainty and lack of consensus on the magnitude of costs (or magnitude of taxes) that future climate consequences will bestow on people (Nordhaus, 1994; Öncüler, 2010; The Economist, 2010). According to a popular climate economic model (Stern, 2006), the cost of future climate consequences, if left unmitigated, could vary between 5% and 20% of global GDP (a large range of variation). Also mentioned above, the NAS panel's estimates varied between 0.8% and 62% of GWP when the panel was asked to assess the cost for a scenario with a rapid 6 degree centigrade rise in the earth's average temperature by 2090 (Nordhaus, 1994).

Although we did not evaluate the effects of costs on people's wait-and-see behavior in our previous study (Dutt & Gonzalez, in press), cost has been shown to have an effect as strong as that produced by time delay (Benzion, Rapoport, & Yagil, 1989; Thaler, 1981). The basic finding is that for problems involving descriptive or hypothetical inter-temporal choices (i.e.,

between paying now and paying in the future), people's discount rate falls sharply when costs increase (Holcomb & Nelson, 1992; Thaler & Loewenstein, 1992). This observation means that given a choice to pay a \$10 carbon tax now or a \$15 carbon tax in a year from now, a majority of people might prefer to pay the later \$15 tax; however, if given a choice to pay a \$100 carbon tax now or a \$150 tax in a year from now, a majority of people might prefer to pay \$100 right now. The main reason for this observation is that people are not only sensitive to relative differences in amounts they have to pay now and in the future, but they are also sensitive to the *absolute differences* in magnitudes between what they pay now and in the future (Prelec & Loewenstein, 1991). Thus, we hypothesize:

**H3a:** In description, the proportion of wait-and-see choices *will be greater* when the cost of consequences is small rather than large.

In addition, although people's discount rate falls sharply when cost increases in *both* experience and description (Johnson & Bickel, 2002); some other studies have also documented a *lack of the effect* of cost in experience (Green, Myerson, Holt, Slevin, & Estle, 2004). Similarly, studies with animals, which only give animals an experience of a cost or reward, seem to find no effect on animals' discount rates (Jimura, Myerson, Hilgard, Braver, & Green, 2009). The main reason for this lack of consistency of the effect in experience is that an animal or human has to actually *wait* to pay a cost or to receive a reward, and such time delays are absent in a descriptive account of the same choice problem (Jimura et al., 2009). Thus, we hypothesize that:

**H3b:** In experience, the proportion of wait-and-see choices should not differ when the cost of consequences is either small or large.

## 8.4 Method

Participants were randomly assigned to one of two conditions: *description* or *experience*. In the *description* condition, participants read a written description of climate consequences and were asked to choose between two options that were each associated with a particular cost, timing, and probability values ( $N = 43$ ). In the *experience* condition, participants sampled two different options that were presented as unlabeled buttons as many times as they wanted to (with no costs), and were then asked to choose one of the two options as their real choice ( $N = 44$ ). Thus, in the experience condition, the cost, timing, and probability of climate consequences were not explicitly provided but were experienced according to the participants' sampling. In both conditions, one option reflected the wait-and-see (risk-seeking) choice and the other option, the act-now (risk-averse) choice.

In both experience and description conditions, each participant received eight problems in random order, where the wait-and-see option in different problems differed according to the cost, timing, and probability of future climate consequences. The cost could be small ( $c=\$18$ ) or large ( $c=\$36$ ), the timing could be early ( $n=10$  years) or late ( $n=60$  years), and the probability could be low ( $p=0.20$ ) or high ( $p=0.80$ ). In all eight problems, the act-now option always presented participants with a \$6 carbon tax which they would need to pay immediately and with certainty. In addition to the tax payment in the wait-and-see option in different problems, participants earned an interest at a rate of 2% per year on a \$5 balance (their salary) in their bank account for each year elapsed in both the experience and description conditions. For an early timing of climate consequences, the balance in the bank increased to \$6.09 and for a late timing of climate consequences, the balance increased to \$16.41. The carbon tax (\$18 or \$36) that participants had to pay due to the early and late climate consequences at the end of the time elapsed was adjusted

in the accumulated bank balance. The net amount of the carbon tax minus the accumulated bank balance was the cost of climate consequences to participants (see below for more details).

#### **8.4.1 The description condition**

One of the eight problems used in the description condition is shown in Figure 8-1 (other problems were identical in form to the example shown, but with different cost, timing, and probability values). The wait-and-see and act-now options were randomly assigned to be shown on the left or right of the computer screen. A participant read and chose one of the two options in each of the eight problems, presented one-by-one in random order. In the act-now option (i.e., option 1 in Figure 8-1), a person had to pay a one-time carbon tax of \$6 now for sure. Thus, upon selecting the act-now option, a person started with a \$5 balance in his bank account, did not get any interest on his \$5 balance, and was to pay a \$1 cost (i.e., \$5 balance + \$0 interest - \$6 tax payment = \$1). In contrast, in the wait-and-see option, a person had to pay a one-time cost of \$X (=18 for a small tax or =36 for a large tax) with a probability P (=0.20 for low or =0.80 for high) Y years from now (=10 in the early timing or =60 in late timing), or \$0 otherwise. As previously mentioned, the value of time Y determined the interest that a participant got on his initial \$5 bank balance. At 2% per annum when Y=10 years, the interest amount was \$1.09, and at 2% per annum for Y=60 years, the interest amount was \$11.41. Therefore, participants paid a cost of \$5 + \$1.09 - \$X (where, X = 18 for a small tax and X = 36 for a large tax with a probability P, and X=0 otherwise) for early timing, and participants paid a cost of \$5 + \$11.41 - \$X (where, X = 18 for a small tax and X = 36 for a large tax with a probability P, and X=0 otherwise) for late timing. As shown in Figure 8-1, participants in the description condition were shown a written description of their initial \$5 bank balance, interest, tax, and the values of Y and P.

Which of these two options will you choose? (Please read the options carefully)

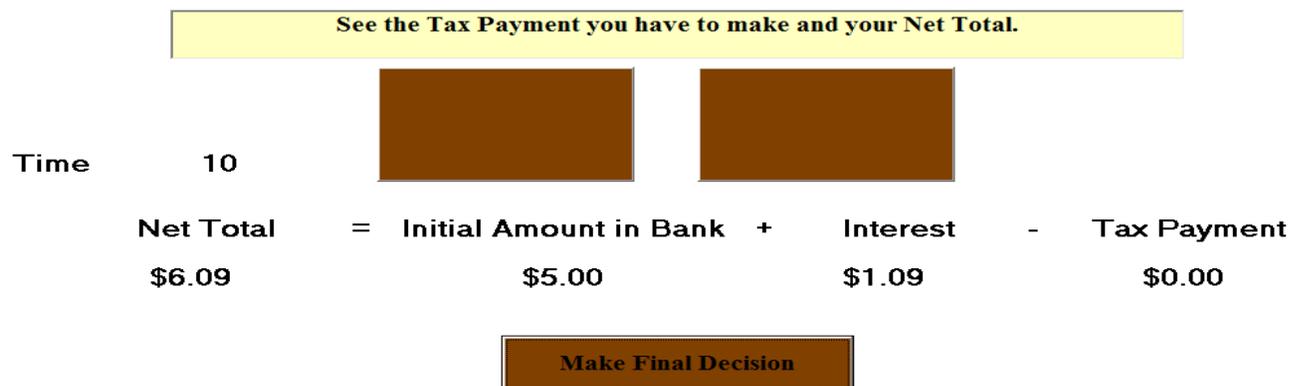
Option2: 10 years from now you pay a one-time carbon tax of \$18 (i.e., net total = $\$5 + \$1.09 - \$18 = -\$11.91$ ) with a 20 in a 100 chance, or you pay a one-time carbon tax of \$0 (i.e., net total = $\$5 + \$1.09 - \$0 = +\$6.09$ ), with a 80 in a 100 chance.	Option1: This year you pay a one-time carbon tax of \$6 (i.e., net total = $\$5 + \$0 - \$6 = -\$1$ ) for sure.
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**Figure 8-1. An example of a problem presented to each participant in the description condition. The problem has a small cost, early timing, and low probability of occurrence of climate consequences.**

#### 8.4.2 The experience condition

In the experience condition, participants clicked upon one of the two unlabeled buttons presented to them in each problem (see Figure 8-2 for an example of a problem given in the experience condition; other problems were presented similarly but with different cost, time, and probability values). Each button in a problem corresponded to one of the two options, act-now or wait-and-see. Clicking on one of the buttons each time gave participants a carbon tax ( $=\$6$ ) if the button was assigned to the act-now option. Thus, upon clicking the act-now button each time, a participant started with a \$5 balance in his account, did not accrue any interest on his \$5 balance, and was to pay a \$1 cost (i.e.,  $\$5 \text{ balance} + \$0 \text{ interest} - \$6 \text{ tax payment} = \$1$ ). In contrast, clicking on the other button gave participants another carbon tax ( $\$X$  and  $\$0$ ). The value of  $\$X$  could be either \$18 if the cost was small, or \$36 if the cost was large. Furthermore, clicking the wait-and-see option delayed the presentation of the carbon tax by a certain number of years, depending on the timing ( $Y=10$  years, if timing was early, or  $Y=60$  years, if timing was late). One year corresponded to one second of real-time delay in the wait-and-see option. The one-second to one-year correspondence is motivated from previous time-preference studies with primates where a similar magnitude of delay had been used (Dutt & Gonzalez, in press;

McClure, Ericson, Laibson, Loewenstein, & Cohen, 2007). Just like in the description condition, the value of time Y determined the interest that a participant got on his initial \$5 bank balance: when Y=10 years, at 2% per annum, the interest amount was \$1.09, and for Y=60 years, at 2% per annum, the interest amount was \$11.41. Thus, for the early timing, participants paid a cost of \$5 + \$1.09 - \$X, and for the late timing, participants paid a cost of \$5 + \$11.41 - \$X. As shown in Figure 8-2, participants were presented with their initial \$5 bank balance, interest, tax, and the values of Y and P as an experience based upon their choice for one of the two button options. Participants were first encouraged to sample both buttons as many times as they wanted (without any cost to them) to gain experience in a problem. Sampling essentially meant clicking on one of the two buttons to find the interest, carbon tax, and the cost that a participant would have to pay and to experience the corresponding time delay (without actually paying any cost for real). A participant was asked to make a final choice by clicking the “Make Final Decision” button after he was satisfied with his sampling. A final choice for the wait-and-see option in a problem allowed participants to earn money as interest in their bank account depending on the timing and to observe the cost at the end of time delay. A final choice for the act-now option in a problem did not give participants any money as interest in their bank account while they observed the cost immediately.



**Figure 8-2. An example of a problem presented to each participant in the experience condition. The problem has a small cost, early timing, and low probability of occurrence of climate consequences. The two choice options in the problem were presented as two blank buttons that could be sampled many times by clicking in the buttons. Once a participant had sampled both buttons many times (without any cost to him), a final decision could be made by clicking the “Make Final Decision” button followed by the button the participant wanted to choose. Sampling a button showed the Net total, Initial Amount in Bank, Interest, and Tax Payment at the end of a time period. The participants had to wait for certain number of years (1 year simulated as 1 second of time delay) to get to know their carbon tax payment in the wait-and-see option. The Net total and Interest updated after the end of each year of wait in the wait-and-see option while the Tax Payment was updated and shown to participants at the end of their period of wait under the wait-and-see option. The Net Total, Initial Amount in Bank, Interest, and Tax Payment were displayed instantaneously (i.e., without any wait) in the act-now option.**

### **8.4.3 Participants**

Eighty-seven undergraduate and graduate students at Carnegie Mellon University participated in this experiment. Participants were recruited through a website advertisement that asked them to participate in a climate decision study. Forty-six participants were males. Ages ranged from 18 years to 59 years ( $M = 26$ ,  $S.D. = 8$ ). All participants started with \$5 base pay and depending upon their final choice in eight different problems they could win or lose money. In both conditions, only a participant’s final choice affected his final payment (thus sampling the button options in experience did not cost participants). Participants were told about this fact in instructions before starting the experiment. Based upon different carbon taxes and interest amounts, the cost to participants could be \$1 in the act-now option in each of the eight problems and one of -\$6.09, -\$16.41, \$11.91, \$1.59, \$29.91, or \$19.59 in the wait-and-see option in a problem (a negative sign with a cost indicates a gain). To pay participants, the amount obtained as a result of participants’ final choices in each of the eight problems was added together to generate a total amount. Then, this total amount was scaled in a ratio of \$10 in the experiment to \$1 in real money and paid to participants. Participants were told that the final earnings in the

experiment will be determined by the 10:1 ratio and their total amount across different problems depending upon their final choices. Participants were shown their total amount and the tax consequences of their final choices in each of the eight problems only at the end of the experiment (to avoid any learning effects).

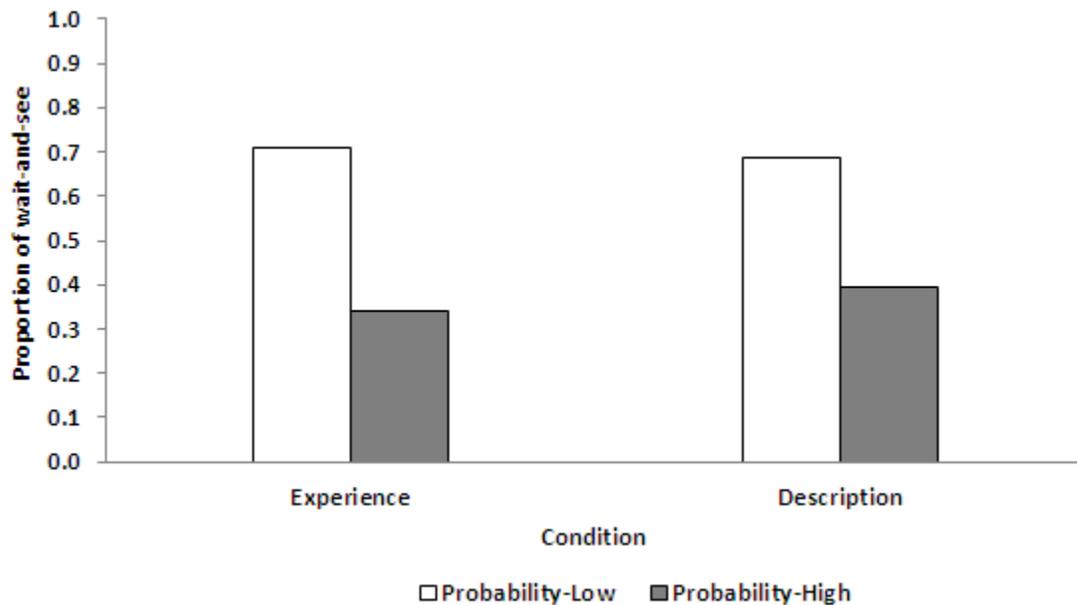
#### **8.4.4 Procedure**

Participants were randomly assigned to one of the two conditions, experience or description. They read instructions that appeared on a computer terminal. The experimenter answered any questions about the instructions before participants could begin. As part of instructions, participants were explained the breakup of different monetary amounts in each problem (e.g., initial amount in their bank account in each problem, interest earned in each problem under the wait-and-see option, and about the possibility of paying a carbon tax in each problem). Also, participants were told that they will get a base pay of \$5. No participant took more than 15 minutes to complete the eight problems in each condition, description and experience.

#### **8.5 Results**

To test H1, we compared the difference between the proportion of wait-and-see choices in the low probability problems ( $p=0.20$ ) and the proportion of wait-and-see choices in the high probability problems ( $p=0.80$ ) within the experience and description conditions, respectively. Figure 8-3 presents the proportion of wait-and-see choices according to the probability of occurrence of the tax consequences (low or high). In experience, there was a significant difference in the proportion of wait-and-see choices when the probability was low (71%) compared to when the probability was high (34%),  $\chi^2(1) = 48.14, p < .001, r = .37$ . Similarly, in description, there was a significant difference in the proportion of wait-and-see choices when the

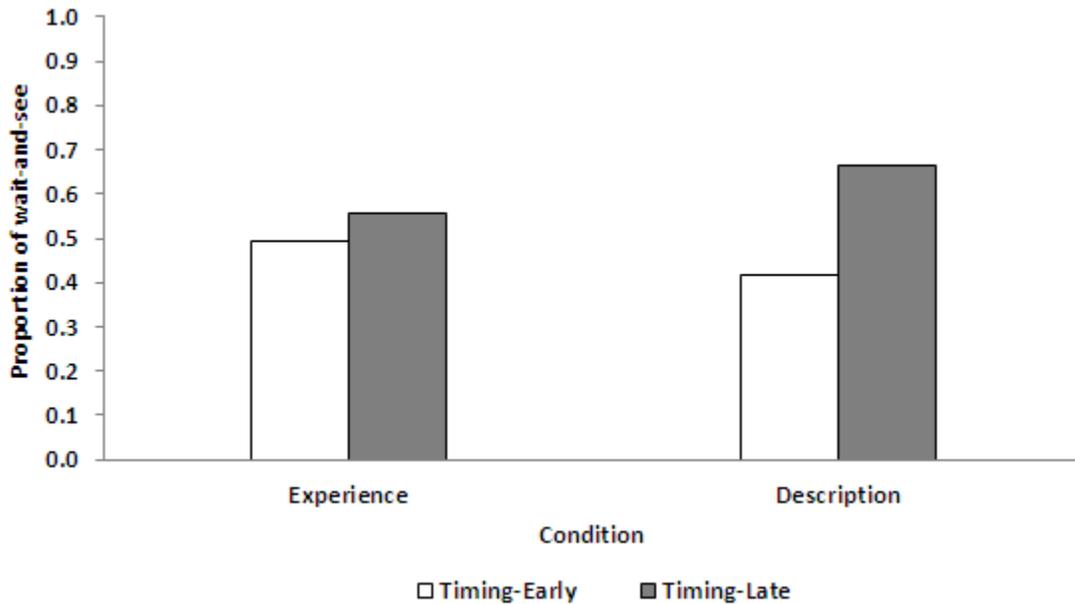
probability was low (68%) compared to when the probability was high (40%),  $\chi^2(1) = 30.42$ ,  $p < .001$ ,  $r = .29$ . Furthermore, according to our expectation in H1, the difference between the low and high probability (71%-34%=37%) in the experience condition was greater than the difference between the low and high probability in the description condition (68%-40%=28%) (due to the effect size,  $r_{\text{experience}} (= .37) > r_{\text{description}} (= .29)$ ). Thus, these results are in the direction of our expectation in H1.



**Figure 8-3. The proportion of final wait-and-see choices in the experience and description conditions according to the probability that future climate consequences (low or high) may occur.**

To test H2, we compared the proportion of wait-and-see choices in problems where the timing was early (Y=10 years) or late (Y=60 years), within the experience and description conditions respectively. Figure 8-4 presents the proportion of wait-and-see choices according to the timing of the climate consequences (early or late). In experience, the difference in the proportion choices when the timing of consequences was early (50%) than when late (56%) was not significant,  $\chi^2(1) = 1.38$ ,  $ns$ ,  $r = .06$ . However, in description, the difference in the

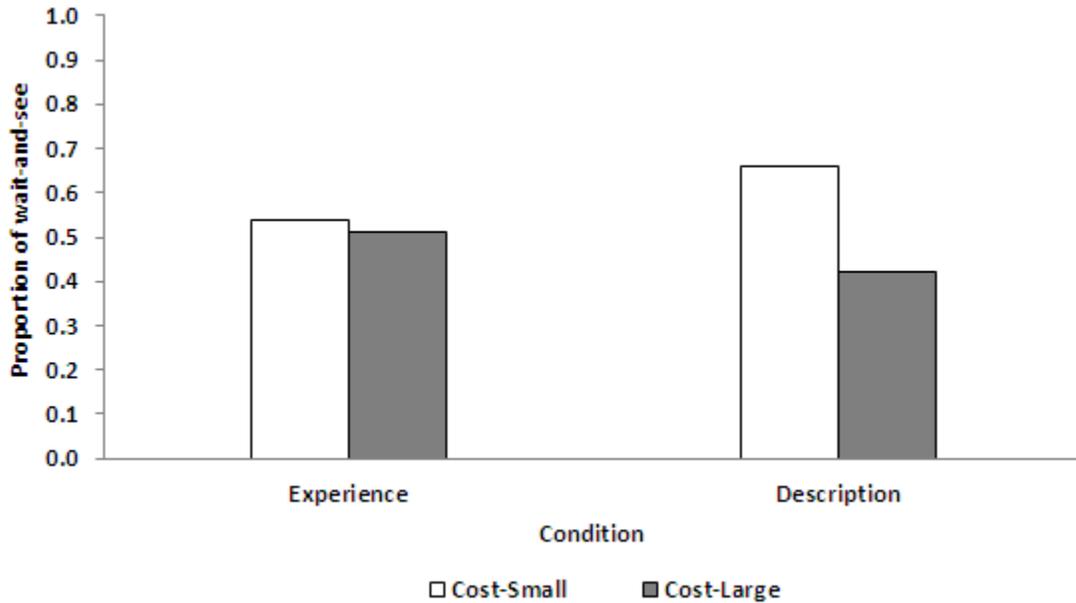
proportion of wait-and-see choices when the timing of consequences was early (42%) than when late (67%) was significant,  $\chi^2(1) = 21.62, p < .001, r = .25$ . Therefore, a greater proportion of wait-and-see choices for later timing (H2) is supported in the description condition and not supported in the experience condition.



**Figure 8-4. The proportion of final wait-and-see choices in the experience and description conditions according to the timing of the climate consequences (early or late).**

Finally, to test H3a and H3b, we compared the proportion of wait-and-see choices in problems where the carbon tax was small ( $X=\$18$ ) or large ( $X=\$36$ ), within the description and experience conditions respectively. Figure 8-5 presents the proportion of wait-and-see choices according to the cost of the climate consequences (small or large). In experience, the difference in the proportion of choices when the cost of consequences was small (54%) than when large (51%) was not significant,  $\chi^2(1) = 0.29, ns, r = .03$ . Therefore, this result in experience supports our expectation in H3b. However, in description, the difference in the proportion of wait-and-see choices when the cost of consequences was small (66%) than when large (42%) was significant,

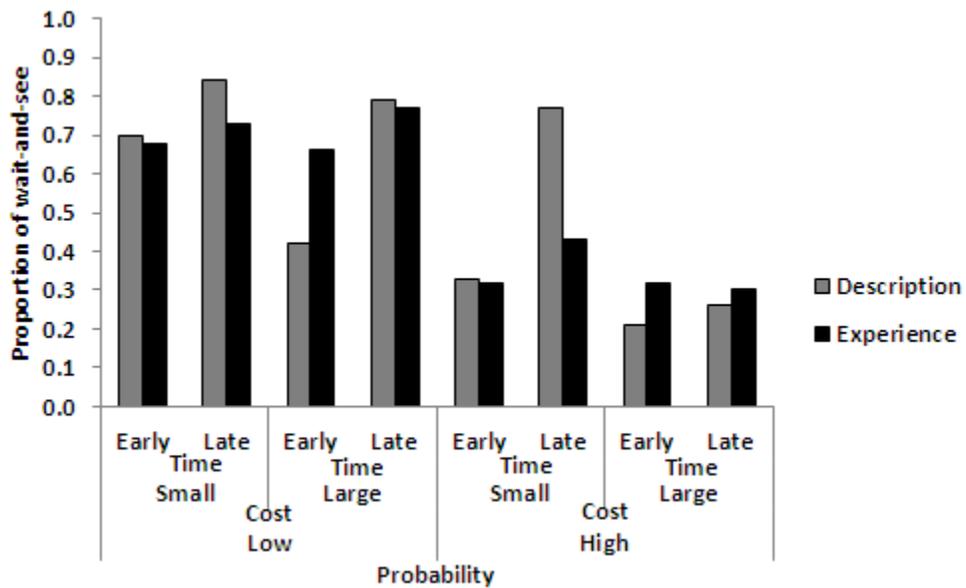
$\chi^2(1) = 19.66, p < .001, r = .24$ . Therefore, this result in description also supports our expectation in H3a.



**Figure 8-5. The proportion of final wait-and-see choices in the experience and description conditions according to the cost of the climate consequences (small or large).**

Although we did not have a prediction about the interaction between the cost, timing, and probability of future climate consequences, we present the joint effects in Figure 8-6. The figure shows the proportion of wait-and-see choices in each of the eight problems used in the experiment. Similarly, Table 8-1 shows the proportion of wait-and-see choices between experience and description conditions in the eight problems along with statistical differences. The proportion of wait-and-see choices was greater in the experience than in the description condition when the probability of consequences was low, cost was large, and timing was early. In contrast, the proportion of wait-and-see choices was smaller in the experience than in the description condition when the probability of consequences was high, cost was small, and timing was late. In all other combinations of probability, cost, and timing, the difference in the proportion between experience and description conditions was not significant. These results

suggest that if the cost, timing, and probability align together to support the proportion of wait-and-see choices in one of the experience or description conditions (based upon their individual effects in Figures 8-3, 8-4, and 8-5), the difference in the proportion of wait-and-see choices between description and experience conditions becomes significant. However, when one or two of the three factors opposes the effect of the remaining factors, the difference in the proportion of wait-and-see choices between experience and description conditions is not significant.



**Figure 8-6. The proportion of final wait-and-see choices in the experience and description conditions as a function of the probability (low or high), time (early or late) and cost (small or large) of the occurrence of climate consequences.**

**Table 8-1. The proportion of wait-and-see choices between experience and description conditions in the eight problems.**

Values of Variables			Problems	Proportion of Wait-and-see (%)		Difference between Experience and Description	
Probability	Cost	Timing	Wait-and-see Option <sup>1</sup>	Act-now Option	Experience	Description	Statistics
Low	Small	Early	-11.91,0.2 and 6.09,0.8	-1,1.0	68	70	-02 ( $\chi^2$ (1) = 0.13, <i>ns</i> , <i>r</i> = .04)
Low	Small	Late	-1.59,0.2 and 16.41,0.8	-1,1.0	73	84	-11 ( $\chi^2$ (1) = 1.54, <i>ns</i> , <i>r</i> = .13)
Low	Large	Early	-29.91,0.2 and 6.09,0.8	-1,1.0	66	42	<b>+24</b> ( $\chi^2$ (1) = 5.06, <b><i>p</i> &lt; .050</b> , <i>r</i> = .24)
Low	Large	Late	-19.59,0.2 and 16.41,0.8	-1,1.0	77	79	-02 ( $\chi^2$ (1) = 0.41, <i>ns</i> , <i>r</i> = .02)
High	Small	Early	-11.91,0.8 and 6.09,0.2	-1,1.0	32	33	-01 ( $\chi^2$ (1) = 0.01, <i>ns</i> , <i>r</i> = .01)
High	Small	Late	-1.59,0.8 and 16.41,0.2	-1,1.0	43	77	<b>-34</b> ( $\chi^2$ (1) = 10.19, <b><i>p</i> &lt; .001</b> , <i>r</i> = .34)
High	Large	Early	-29.91,0.8 and 6.09,0.2	-1,1.0	32	21	+11 ( $\chi^2$ (1) = 1.33, <i>ns</i> , <i>r</i> = .12)
High	Large	Late	-19.59,0.8 and 16.41,0.2	-1,1.0	30	26	+04 ( $\chi^2$ (1) = 0.71, <i>ns</i> , <i>r</i> = .04)

Note. <sup>1</sup>The wait-and-see option where a cost occurred with a probability *p* and an interest amount occurred with a probability, 1- *p*, i.e., in the absence of a carbon tax (e.g., get -\$1.59 with a 20% probability and get \$16.41 with an 80% probability in the second row of the table).

## 8.5.1 Sampling in experience

Across all the eight problems in the experience condition, participants sampled both options less than five times on average. Although timing and cost did not affect how many times either options were sampled, the probability did affect the number of samples of the act-now option. Consequently, the number of samples across both options was no different for early or late timing (for act-now option:  $\text{mean}_{\text{early}} (4.5) = \text{mean}_{\text{late}} (1.9)$  with  $z = -1.90$ ,  $ns$ ,  $r = -.10$ ; for wait-and-see option:  $\text{mean}_{\text{early}} (2.0) = \text{mean}_{\text{late}} (1.6)$  with  $z = -1.23$ ,  $ns$ ,  $r = -.07$ ). As a delay was present on the wait-and-see option, this result for that option shows that participants did not perceive the timing as a cost, where a time-cost perception could have dithered them from sampling the wait-and-see option (like in Dutt & Gonzalez, in press, where time delay in the wait-and-see option did not provide any incentive to people). Similarly, the number of samples of both options was no different for a small or large cost (for act-now option:  $\text{mean}_{\text{small}} (4.2) = \text{mean}_{\text{large}} (2.1)$  with  $z = -0.54$ ,  $ns$ ,  $r = -.03$ ; for wait-and-see option:  $\text{mean}_{\text{small}} (1.8) = \text{mean}_{\text{large}} (1.7)$  with  $z = -0.06$ ,  $ns$ ,  $r = -.00$ , respectively). Furthermore, as mentioned above, the number of samples of the act-now option was affected by the probability of consequences, low or high ( $\text{mean}_{\text{low}} (4.7) \gg \text{mean}_{\text{high}} (1.7)$ :  $z = -4.07$ ,  $p < .001$ ,  $r = -.22$ ); whereas the number of samples of the wait-and-see option was unaffected by probability ( $\text{mean}_{\text{low}} (1.8) = \text{mean}_{\text{high}} (1.8)$ :  $z = -0.39$ ,  $ns$ ,  $r = -.02$ ). Therefore, when the probability of consequence was low on the wait-and-see option, participants sampled the act-now option more often before making their final choices.

Hertwig et al. (2004) suggested that one main reason why probability of consequences affects participants' risk-seeking behavior is limited information search or limited samples of the two options. The smaller the number of samples from the wait-and-see (risk-seeking) option, the larger the chance that a participant will not come across the low probability consequence.

Consequently, the participant will remain ignorant of the existence of the low probability consequence. Indeed, the small sample size in different problems made participants observe the low probability consequence at less than its expected probability. Table 8-2 provides the proportion of wait-and-see choice in different problems as a function of the frequency of observing a low probability consequence as being less than, more than, or equal to its expected value (the median sample size for each option in each problem has been listed in brackets in Table 8-2 and depicts participants' small sample sizes). The expected value is determined by the product of "n," the number of times the wait-and-see option is sampled by a participant in a problem, and "p," the true probability of observing a low probability consequence in the problem. The table shows these percentages for different problems, where the monetary consequences in the two options, the probability of the wait-and-see consequence, and the low probability consequence are clearly labeled. When the probability of a negative consequence was low, there was a clear evidence of people behaving as if the low probability negative consequence had less impact than it deserved according to its objective probability (irrespective of the timing and cost): The proportion of wait-and-see choices, where the low probability was encountered less frequently than expected, was greater than the proportion of wait-and-see choices where the low probability was encountered as or more frequently than expected (76% > 53%, 76% > 67%, 73% > 29%, and 85% > 55%). Similarly, the proportion of wait-and-see choices, where the low probability positive consequence was encountered less frequently than expected, was consistently smaller than the proportion of wait-and-see choices where the low probability positive consequence was encountered as or more frequently than expected (38% > 31%, 80% > 24%, 60% > 17%, and 53% > 17%). These observations, which indicate participants' limited information search, is an explanation for the significantly greater proportion

of wait-and-see choices in the experience condition when the probability of the negative consequence was low, and a significantly smaller proportion of wait-and-see choices in the experience condition when the probability of the negative consequence was high (see Figure 8-6).

## **8.6 Discussion**

This research contributes to a better understanding of people's choice to wait-and-see rather than acting now in a climate problem according to how that decision is made (from description or experience). We replicated the effects of the probability of future climate consequences in experience and description from Dutt & Gonzalez (in press); and also demonstrated that cost and timing of future consequences have an effect on people's wait-and-see choices when decisions are made from description, but not from experience.

The amplification of the difference between low and high probability in experience is explained by people's risky choices in decisions from experience: they are risk-seeking and choose wait-and-see more for low probability consequences, and they are risk-averse and choose wait-and-see less for high probability consequences. While making decisions from experience, people behave as if the low probability consequences have less impact than they deserve according to their objective probabilities, and the high probability consequences have more impact than they deserve (Hertwig, in press). Similarly, the attenuation in description is explained by people's risky choices in decisions from description: they are risk-averse for low probability consequences and they are risk-seeking for high probability consequences (Hertwig, in press; Tversky & Kahneman, 1992). As in the real world, there exists uncertainty about the true probability of future climate consequences (low or high).

**Table 8-2. The proportion of wait-and-see choices with a low probability consequence as a function of the frequency of the low probability consequence occurring.**

Values of Variables			Problems			Proportion of wait-and-see choice (with low probability consequences)	
Probability	Cost	Timing	Wait-and-see Option	Act-now Option	Low Probability Consequence	# < np <sup>1</sup> %	# ≥ np <sup>2</sup> %
Low	Small	Early	-11.91,0.2 and 6.09,0.8 (1) <sup>4</sup>	-1,1.0 (1)	-11.91,0.2	76 (22/29) <sup>3</sup>	53 (08/15)
Low	Small	Late	-1.59,0.2 and 16.41,0.8 (1)	-1,1.0 (1)	-1.59,0.2	76 (22/29)	67 (10/15)
Low	Large	Early	-29.91,0.2 and 6.09,0.8 (1)	-1,1.0 (1)	-29.91,0.2	73 (27/37)	29 (02/07)
Low	Large	Late	-19.59,0.2 and 16.41,0.8 (1)	-1,1.0 (1)	-19.59,0.2	85 (28/33)	55 (06/11)
High	Small	Early	-11.91,0.8 and 6.09,0.2 (1)	-1,1.0 (2)	6.09,0.2	31 (11/36)	38 (03/08)
High	Small	Late	-1.59,0.8 and 16.41,0.2 (1)	-1,1.0 (1)	16.41,0.2	24 (07/29)	80 (12/15)
High	Large	Early	-29.91,0.8 and 6.09,0.2 (2)	-1,1.0 (2)	6.09,0.2	17 (05/29)	60 (09/15)
High	Large	Late	-19.59,0.8 and 16.41,0.2 (1)	-1,1.0 (2)	16.41,0.2	17 (05/29)	53 (08/15)

Note: <sup>1</sup>Proportion of wait-and-see choices with a low probability consequence, where the low probability consequence was encountered less frequently than expected, i.e.,  $n^*p$ , where  $n$  is the number of samples of the wait-and-see choice performed by a participant and  $p$  is the probability of the occurrence of the low probability consequence. <sup>2</sup>Proportion of wait-and-see choices with a low probability consequence, where the low probability consequence was encountered as or more frequently than expected. <sup>3</sup>Numbers in brackets refer to the actual frequencies of different proportions. <sup>4</sup>This number indicates the median sample size for the option in the respective problem in the experiment.

Experiential methods that communicate this uncertainty might have more impact on current wait-and-see policies for climate change compared to the descriptive methods.

Our results also indicate that the effect of timing is absent in experience, but present in description. In description, we found a greater proportion of wait-and-see choices when consequences occur later in the future compared to earlier. People's thinking seems to be largely driven by the greater gains they can gain as a consequence of the wait when the consequences occur late rather than early.

Similarly, one possible explanation why timing lacked an effect in experience could be that people had to actually wait for the time to elapse, *unlike* people in the description condition. In experience, people may have focused on the interest that grows in their account over time during their wait, rather than on the climate consequences that followed the wait. Not attending to or distinguishing the cost consequences after the early or late timing in experience could diminish the effects of timing. Another possible reason could be the experience of an increase in the interest amount with time in both early and late timing conditions. Participants sampled the wait-and-see option equally in both cases (which is indicated in our sampling results reported above) and later also chose the wait-and-see option with equal chances as their final choice. Thus, experiencing the timing seems to have a moderating effect on people's wait-and-see choices due to the actual delay present in the wait-and-see option under both timing conditions.

The effects of costs are present in the description condition and are absent in the experience condition. In description, a large cost reduced the proportion of wait-and-see choices; whereas such a relationship is absent in the experience condition. People's discount rate fall sharply as the cost increases (Holcomb & Nelson, 1989; Thaler & Loewenstein, 1992). Thus, their disincentive due to a large cost in the wait-and-see option is greater than their disincentive

due to a small cost in the same option. The absence of a similar effect in the experience condition, however, could be because participants in experience needed to wait in order to pay a tax, while they accrued interest that seemed to moderate the effects of large and small taxes. This explanation is further supported by people's sampling of the wait-and-see option in our results: there was no difference in people's sampling behavior for small and large costs. Therefore, sampling was perceived as equally costly for both small and large costs, and thus failed to influence people's final choice for the different magnitudes of costs. Furthermore, our finding of the absence of effects of costs in experience support similar findings in literature involving humans (Green et al., 2004) and animals (Jimura et al., 2009).

Consequently, the descriptive methods seem to have more impact on people's wait-and-see policies for climate change compared to the experiential methods. Thus, reading descriptions about high and low cost alone, or an early and late timing alone carries more impact on people's wait-and-see behavior compared to when the same information about cost or timing is acquired through experiential methods.

Moreover, the joint effects of probability, cost, and timing are interesting because literature in JDM has considered the influence of probability presented as a description or as an experience on people's risky choices without also considering the influence of timing or cost (Hertwig et al., 2004; Kahneman & Tversky, 1979). Similarly, JDM research has considered the influence of timing alone or of timing and probability in decisions from description and experience without considering the influence of cost (Dutt & Gonzalez, in press; Hayden & Platt, 2007; Loewenstein & Elster, 1992; Luhmann et al., 2008; Madden, Begotka, Raiff, & Kastern, 2003; Mischel & Grusec, 1967; Thaler, 1981). Our results show that the proportion of wait-and-see choices is higher in experience compared to description when the probability is low, cost is

large, and timing is early; however, this proportion is smaller in experience when the probability is high, cost is small, and timing is late. This result may be explained through the effect of the probability in both the experience and description conditions, and the strong and weak effects of timing and cost on both conditions, respectively. The differences in the proportion of wait-and-see choices are affected by all three factors.

Descriptive methods of risk communication might produce more wait-and-see behavior when uncertain climate information communicates a high probability, small cost, and late timing for future consequences; whereas, experiential methods of risk communication might produce more wait-and-see behavior when the information communicates a low probability, large cost, and early timing for future consequences. Future research that applies JDM principles to climate change would benefit by building upon the findings of this study.

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## **Chapter 9: Conclusions, Policy Recommendations, and Future Directions**

### **9.1 Conclusions**

This thesis builds a framework of people's wait-and-see behavior on climate change due to the interplay of a number of cognitive factors that are peculiar to human beings. The results in this thesis show that cognitive factors like misperceptions of feedback, correlational or linear thinking, and risk- and time- preferences influence people's wait-and-see behavior about policies that mitigate climate change. According to this thesis, due to misperceptions of feedback, people ignore the feedback delays between climate mitigation actions and their associated consequences and this ignorance results in wait-and-see behavior. Moreover, thinking linearly, people tend to underestimate the actual nonlinear accumulation of greenhouse gases in Earth's atmosphere. This underestimation is likely to result in people undervaluing the urgency of the climate change problem thus resulting in wait-and-see behavior. Furthermore, the same information about the timing, probability, and cost of consequences, when gathered descriptively or experientially, has a differential impact on people's wait-and-see choices. According to this thesis, descriptive methods are likely to produce more wait-and-see behavior when information communicates a high probability, small cost, and late timing for future consequences; whereas, experiential methods are likely to produce more wait-and-see behavior when information communicates a low probability, large cost, and early timing for future consequences.

There is little doubt that climate change will become a serious problem for society if we decide to postpone mitigation actions to a time in the future (IPCC, 2007b; Sterman, 2008). Therefore, in order to make people act on climate change in the status quo, we must propose education policies that correct people's misperceptions about climate processes. According to this thesis, repeated feedback in simulation tools (like DCCS) about the consequences of setting

different CO<sub>2</sub> emission policies helps people to improve their control of CO<sub>2</sub> concentration over many trials. Thus, both during policymaking on climate and while imparting climate education in schools, it would be desirable to incorporate the use of simulation tools that supplement normal methods of policymaking and education. In this regard, the repeated feedback manipulation is also likely to help people to make energy efficient decisions that save electrical energy in their households. For example, imagine an air conditioner with a meter display that tells people how much time it has been running and how much energy and money it has accumulated since the first day of the month. Such an intervention that provides repeated feedback about energy and money used is likely to make people conscious of the cause-and-effect relationship between their decision to use the air conditioner and the corresponding high cost consequences in their monthly electric bill. As people are likely to avoid high costs, the end result is likely to be an efficient use of the air conditioner that saves energy.

Policies that supplement the use of repeated feedback in simulation tools with normal methods are good, but these policies also need to be sensitive to the differential needs of people with and without backgrounds and education in science and mathematics. In this regard, this thesis suggests further research that investigates the design of certain background-specific features as part of these tools which when incorporated are likely to benefit people with science and non-science backgrounds equally.

Furthermore, this thesis suggests the use of physical representation (which represents a problem using a picture that acts as a metaphor) as an effective method of representing different climate and non-climate problems compared to text and mathematical graphs. For example, a physical representation that shows the energy inflow and outflow in the U.S. using a picture is likely to be very useful to policymakers in order to target specific sectors of the economy (e.g.,

industrial or transportation) for energy efficiency. Similarly, physical representation is also likely to succeed in conserving Earth's natural resources. For example, in 2008, the City of New York and partners launched an advertising campaign to promote recycling awareness in the city. The campaign used physical representation involving metaphor and analogy by comparing the huge amount of recyclable paper thrown away in New York City annually to be equivalent to filling the entire Empire State Building. The advertisement created a "picture" of the iconic skyscraper composed entirely of discarded magazines and catalogs (i.e., a physical representation), and this metaphor enabled people to improve their recycling behavior.

Given these successes, the physical representation manipulation also seems promising considering the fact that unlike a simulation tool that needs a computer machine, the physical representation does not require a computer to be projected, rather it could be drawn on a piece of paper (as the experiments in this thesis and the New York City advertisement campaign do). Thus, the physical representation could be directly used in climate reports and newspapers without any need of computer technology to accompany these publications. Consequently, it is likely that the physical representation has a greater societal reach considering that in many parts of the developing and underdeveloped world, the advent of computer technology and internet is still a distant dream, and in these places, people gather most of their news from newspapers and other printed material.

This thesis also suggests that often times it might be difficult to change people's reliance on cognitive factors and here aligning problems with people's reliance on these factors (like linear thinking) is likely to enable a majority of them to make ecofriendly decisions. Such interventions, that target and use people's reliance on cognitive factors to improve their decision making, are likely to enable proliferation of ecofriendly policies (e.g., eco-taxes) that benefit

society and that are less problematic in terms of gathering public support (as they don't change the way people think). Also, the power of this information presentation manipulation is that the same manipulation can be used for many different societal problems that the world faces day-to-day: pollution in river and seas, cigarette smoking, and throwing garbage in public places etc.

Finally, the impact of people's risk- and time- preferences on people's wait-and-see choices have important implications towards how risks about future climate consequences are communicated using experiential methods (e.g., movies, pictures, computer simulations etc.) and descriptive methods (e.g., newspapers, media reports, magazines, books etc.). From the overall results in this thesis, the descriptive methods seem to have more impact on people's wait-and-see choices compared to the experiential methods; therefore, reading written descriptions about high and low cost alone, or an early and late timing alone is likely to carry more impact on people's wait-and-see behavior compared to when the same information about cost or timing is acquired through experiential methods. However, depending upon the nature of communication, its content, and the policymaker's intention, either of the two methods is likely to be effective in manipulating people's wait-and-see behavior. An important challenge for climate policy is how to closely monitor the descriptive and experiential impacts of these methods as these methods have tremendous potential to make people act in the status quo on climate change.

## **9.2 Policy Recommendations**

There is substantial scientific evidence that climate change would occur with catastrophic consequences in the near future if we continue on a path of increasing greenhouse gas emissions (IPCC, 2007a; 2007b). The 1992 Rio Declaration on Environment and Development (UNCED, 1993, Article 15) gave the world the "precautionary principle" for resolving the climate change problem: "a lack of full scientific certainty should not be used to justify postponing cost-effective

measures in the face of threat of serious or irreversible harm.” From a public-policy perspective, given the uncertainties present in the probability, timing, and cost magnitudes of future climate consequences, many people advocate that we should follow a precautionary approach to climate change and that policies should be such that they cause people to act on climate change rather than exhibit wait-and-see behavior (Spratt & Sutton, 2008). Therefore, policy interventions suggested here are those that enable people to improve their understanding of Earth’s climate and its processes, enable them to reduce their wait-and-see behavior, and enable them to make decisions that benefit the environment. Based upon the results and conclusions drawn in this thesis, the following recommendations are likely to be beneficial:

1. The use of simulation tools (like DCCS) in climate education that provide repeated feedback about actions and their associated consequences.
2. Sensitivity to and cognizance of the differential effects that these simulation tools are likely to produce for people with and without science and mathematics education and backgrounds.
3. The use of physical representation that represents a problem using a picture and that acts as metaphor. The physical representation is likely to reduce people’s misconceptions related to correlational thinking and violation of mass balance.
4. As much as possible, designing choices for people that align with their cognitive factors (e.g., linear thinking). This information presentation is likely to enable people to make decisions that help the environment without any change in the way they think about these problems.
5. Finally, both descriptive and experiential methods should be used to communicate the risks of future climate change. However, as the impacts of presenting information about

consequence, probability, and timing are opposite in both these methods, this communication should be carefully designed to aid a reduction in people's wait-and-see choices.

### **9.3 Scope and Limitations**

This thesis research is limited to the study of individual decision makers. Thus, for the purpose of this thesis, the main focus has been on a single decision maker whose choices influence decisions at a higher societal level. As climate policies are formulated by people with science and policy backgrounds (Nordhaus, 1994), an important question to consider is whether this research distinguishes between people with and without policy backgrounds and people with and without science backgrounds? The simple answer is that this research has indeed tried this distinction in different papers (Dutt & Gonzalez, 2011a; 2011c). For example, Dutt and Gonzalez (2011a) have distinguished between people from sciences and mathematical backgrounds (STEMs) and those from the arts and social sciences backgrounds (non-STEMs). The idea is that policymaking on climate change occurs in “informed” groups in the real world and a critical finding is that to be able to benefit from manipulations of feedback, it is better if one possesses a scientific background (this was found in Dutt & Gonzalez, 2011a). Similarly, Dutt and Gonzalez (2011c) have distinguished between people from policy backgrounds (who are more suited to positions taken by policymakers) compared to people with general backgrounds. The conclusion from that research is that having a background policy does not help improve performance of these backgrounds over the general backgrounds. However, as this research was undertaken using resources available at the university level and due the difficulty of finding and questioning real policymakers, the scope of this research is confined to the distinction between STEMs and non-STEMs backgrounds and policy and general backgrounds. Thus, in this research,

background serves as a proxy for the actual decision maker, e.g., policymakers, laypeople, nonscientists, and scientists.

Another important point to consider is whether this research focuses on groups of decision makers. The boundary and conclusions of this research are currently restricted to a single decision maker. That said, I do agree that the social dynamics, that arises from group behavior, is also extremely important and something to try in the future. When people make choices on climate problems in groups rather than as single individuals, there could be a conflict of interest between one person's choices for an option with the other person's choices. Also, in this regard, a person might not be able to accomplish his or her individual choice due to a group's consensus decision. Here, the role of people who possess power in the group to make a final decision becomes important and this role needs to be considered as part of the decision making process. However, if groups are completely democratic and decisions in groups are made by consensus with individuals possessing equal power status, then these consensus decisions are likely to be better compared to those that are made by single individuals. In fact, this expectation for democratic groups is likely to be true from some real world evidence as well: In the program, *Who Wants to be a Millionaire?*, often times single decision makers benefit in their decision choices by asking for an audience poll (which is a consensus decision of many people).

On another point, this thesis has considered the role of cognitive factors that influence people's wait-and-see behavior and its conclusions are restricted to the cognitive factors described above. This thesis focused on the cognitive factors because the interplay of these factors has been downplayed in till recently (APA, 2009). However, one can argue that this thesis did not consider the role of motivational factors (e.g., political ideology, perceptions of needs versus luxuries, core psychological needs, and attachment to a place etc.) which are also

likely to influence wait-and-see behavior on climate change. However, the role of motivational factors has been part of recent research and has been studied much more compared to cognitive factors (APA, 2009; Hardisty, Johnson, & Weber, in press). For example, Hardisty et al. (2009) have experimented with a framing manipulation and shown that people's political ideology (a motivational factor) interact with the framing effect. These researchers polled a large national sample about a program that would raise the cost of certain products believed to contribute significantly to climate change (such as air travel and electricity) and use the money to fund alternative energy and carbon capture projects. The identical program was described as a "carbon tax" to half the respondents, and as a "carbon offset" to the other half. More liberal individuals did not discriminate between the two frames (meaning, they were equally likely to support the program regardless of the label used), but more conservative individuals strongly preferred the carbon offset to the carbon tax. as part of future research, I would like to consider how motivational factors (like political ideology) interact with the cognitive factors to influence people's wait-and-see behavior.

Furthermore, although this research in different experiments, tries to best represent the "real world" by using well known climate models and dynamics, the research has the same limitations as every laboratory-based research: it deals with abstractions that might suffer from dissimilarities to real-life social and global decision making settings. Lastly, although this thesis tries to address the interplay of different cognitive factors to explain reasons for people's wait-and-see behavior on climate change, yet this treatment is not exhaustive due to the constraints of time and resources. Thus, still many other manipulations could be tried within the proposed research areas and in other areas.

## 9.4 Topics to Explore in Future Research

Future work in this research program will build upon and further the findings reported in this thesis. Within the confines of the currently considered cognitive factors, one could evaluate the effects of correlational or linear thinking, the effectiveness of the repeated feedback in simulation tool, and the physical representation on groups of decision makers compared to single decision makers. Here, it would be interesting to manipulate individuals' education backgrounds in these groups to be closer to those of policymaking groups that decide on policies on climate change. One possibility is that these groups could be heterogeneous with a mix of science and non-science backgrounds. Another possibility is that these groups could be homogenous with only people from one of the two backgrounds. Similarly, one could think of certain features in the DCCS that could benefit non-STEMs equally as they do to STEMs. Some of these features could be simply providing more trials of training on the same climate problem or more heterogeneous training on different problems for the same number of trials to non-STEMs compared to STEMs. However, one could also think of certain decision aids incorporated into DCCS that make the cause-and-effect relationships between decisions and their consequences salient to non-STEMs and indicate the quality of their decisions (correct/incorrect) after every decision made. Other manipulations could include climate problems that are either similar in DCCS and the following paper-and-pencil climate stabilization (CS) task, or that are different between DCCS and the CS task. This design will enable us to test whether people from STEM and non-STEM backgrounds learn the structural features (i.e., cause-and-effect relationships) in these problems, or do they learn the surface features (i.e., similarity of units and values) during their training in DCCS. That is because, if people learn the surface features, then they should perform well in DCCS during their training and perform poorly in the CS task that follows their

training, given that the problems used are different between these two tasks. At the same time, if people learn the structural features, then they should perform well in both DCCS and the CS task, given that the problems are different between these two tasks.

Furthermore, under the theme of risk- and time- preferences, in a future study, it would be interesting to test people's wait-and-see choices on some of the IPCC proposals with different climate cost consequences (e.g., of limiting global mean temperature at 2 degree centigrade increase), or even manipulating the intergenerational issue of "you paying" versus "your children paying" under two separate conditions. Again, here a study of aggregate phenomena in a group setting and its comparison to an individual setting will be interesting to try as part of future.

In order to investigate the area of group decision making on climate change, I have currently run a small pilot experiment that extends the study of people's wait-and-see behavior on environmental problems from a single individual to groups of individuals. Here, I have investigated people's wait-and-see behavior using a game-theoretic negotiation perspective that uses 2x2 games like the prisoner's dilemma and chicken. As part of these games, I propose to make participants that play each other in groups of two come from either the developed or developing world. Therefore, players playing each other could be: developed playing developed, developed playing developing, or developing playing developing in three separate between-subjects conditions. Here, players play each other in groups repeatedly for an unknown number of rounds and decide between an act-now and a wait-and-see choice on climate change in each round. The combination of groups and the repeated play dynamics is representative of groups that come from different developed and developing countries and negotiate upon policies for climate change in meetings held by the U.N. in December every year. The interesting question here is whether participants in the developed – developing condition, after repeated rounds of

negotiations, decide to mutually agree to act on climate change, given that there are going to be in-group and out-group cognitive factors (e.g., in-group favoritism and out-group hate) that might hinder the mutual action.

Finally, beyond this thesis, I would also like to expand my research work to include the interplay of other relevant cognitive and motivational factors in environmental decision-making and how these factors could be used to make ecofriendly decisions. For example, the “framing” of environmental issues has a large impact on whether ecofriendly policies and decisions are acceptable to people. Findings in literature suggest that framing the same decision situation in different ways has differential effects on people’s attention and response to them. Individuals are more receptive when they perceive the information being communicated as having salience, relevance, authority, and legitimacy (Cash et al., 2002). Thus, although the public support for a “carbon-tax” might be limited, people readily adopt a “carbon-offset” or “carbon-credit” (Hardisty et al., in press), where framing cost as a “credit” as opposed to a “tax” makes people more receptive and forthcoming. Similarly, people in India are expected to be more receptive to climate-change impacts when these impacts are communicated as a decrease in snow in the Himalayas, whereas people in Florida are expected to be more receptive when the same climate-change impacts are communicated as hurricanes and floods. I am interested to investigate the use of framing interventions to make people adopt ecofriendly technologies and furthermore curtail their inefficient energy use.

In connection to the role of motivational and cognitive factors, I am also interested to test how these factors come together to influence people’s environmental decisions. For example, while playing DCCS, one is likely to misperceive the feedback delays in the simulated climate system’s inputs and outputs. In such a system, it is interesting to see whether, when people are

motivated by giving them more incentive (money) to control CO<sub>2</sub> concentration at the goal, does this motivation enables them to overcome their cognitive limitations? Also, does a more goal directed motivation like achieve 450 ppmv by year 2050 and in return getting a \$100 Amazon gift card help people to overcome their cognitive limitations? Does this speculation also hold true for non-monetary motivations, e.g., a better for world for our children and grandchildren, or a higher level of ecofriendly commitment from people in our neighborhood?

In the course of my future research, I would like to build upon and extend the research reported in this thesis in order to improve people's decision-making and behavior with regards to the Earth's climate.

## 9.4 References

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## Appendix A: Effectiveness of Physical Representation in STEM/non-STEM Backgrounds and Graduate/Undergraduate Levels of Education in Chapter 4's Experiment 1

**Table A1. The correct accumulation in different time periods and the corresponding average accumulation in the two representations split by STEM and non-STEM backgrounds in Chapter 4's Experiment 1.**

Representation and backgrounds	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	10.0 (0.0) <sup>1</sup>	12.0 (0.0)	16.0 (0.0)	22.0 (0.0)	<b>30.0 (0.0)</b>
Graphical – non-STEM	<b>11.3 (2.3)</b>	13.7 (4.7)	16.7 (6.2)	20.0 (7.6)	<b>24.3 (9.0)</b>
Statistics (comparison to Correct)	<b><math>t(22)=2.3</math>, <math>p&lt;.05</math>, <math>r=0.44^2</math></b>	$t(22)=1.7$ , <i>ns</i> , $r=0.34$	$t(22)=0.5$ , <i>ns</i> , $r=0.11$	$t(22)=-1.3$ , <i>ns</i> , $r=0.27$	<b><math>t(22)=-3.0</math>, <math>p&lt;.01</math>, <math>r=0.54</math></b>
Graphical – STEM	10.0 (2.0)	12.1 (2.3)	15.2 (2.9)	<b>19.5 (5.6)</b>	<b>24.9 (7.7)</b>
Statistics (comparison to Correct)	$t(43)=0.1$ , <i>ns</i> , $r=0.02$	$t(43)=0.2$ , <i>ns</i> , $r=0.03$	$t(43)=-1.8$ , <i>ns</i> , $r=0.26$	<b><math>t(43)=-3.9</math>, <math>p&lt;.001</math>, <math>r=0.51</math></b>	<b><math>t(43)=-4.9</math>, <math>p&lt;.001</math>, <math>r=0.60</math></b>
Physical – non-STEM	09.7 (1.6)	11.7 (1.6)	15.5 (2.1)	21.1 (3.2)	28.6 (4.9)
Statistics (comparison to Correct)	$t(24)=-0.9$ , <i>ns</i> , $r=0.18$	$t(24)=-1.0$ , <i>ns</i> , $r=0.20$	$t(24)=-1.3$ , <i>ns</i> , $r=0.26$	$t(24)=-1.4$ , <i>ns</i> , $r=0.27$	$t(24)=-1.4$ , <i>ns</i> , $r=0.27$
Physical – STEM	10.1 (0.7)	12.1 (0.8)	16.0 (0.8)	21.7 (1.4)	29.3 (2.6)
Statistics (comparison to Correct)	$t(36)=1.0$ , <i>ns</i> , $r=0.16$	$t(36)=0.8$ , <i>ns</i> , $r=0.13$	$t(36)=0.0$ , <i>ns</i> , $r=0.00$	$t(36)=-1.3$ , <i>ns</i> , $r=0.21$	$t(36)=-1.7$ , <i>ns</i> , $r=0.57$

*Note.* <sup>1</sup> The values in bracket represent the standard deviation about the mean. <sup>2</sup> The value indicates the effect size.

**Table A2. The correct accumulation in different time periods and the corresponding average accumulation in the two representations split by graduate and undergraduate level of education in in Chapter 4's Experiment 1.**

Representation and level of education	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	10.0 (0.0) <sup>1</sup>	12.0 (0.0)	16.0 (0.0)	22.0 (0.0)	30.0 (0.0)
Graphical – Undergraduate	10.7 (2.8)	13.3 (4.2)	16.7 (5.1)	20.8 (5.8)	<b>26.0 (7.2)</b>
Statistics (comparison to Correct)	$t(36)=1.6$ , <i>ns</i> , $r=0.04^2$	$t(36)=1.8$ , <i>ns</i> , $r=0.05$	$t(36)=0.8$ , <i>ns</i> , $r=0.02$	$t(36)=-1.2$ , <i>ns</i> , $r=0.03$	<b><math>t(36)=-3.4</math>, <math>p&lt;.001</math>, <math>r=0.09</math></b>
Graphical – Graduate	10.0 (0.8)	11.8 (1.6)	<b>14.6 (2.8)</b>	<b>18.2 (5.1)</b>	<b>23.1 (8.0)</b>
Statistics (comparison to Correct)	$t(29)=0.0$ , <i>ns</i> , $r=0.00$	$t(29)=-0.6$ , <i>ns</i> , $r=0.02$	<b><math>t(29)=-2.8</math>, <math>p&lt;.01</math>, <math>r=0.10</math></b>	<b><math>t(29)=-4.1</math>, <math>p&lt;.001</math>, <math>r=0.14</math></b>	<b><math>t(29)=-4.7</math>, <math>p&lt;.001</math>, <math>r=0.16</math></b>
Physical – Undergraduate	09.8 (1.4)	11.7 (1.4)	15.6 (5.1)	21.2 (2.8)	28.7 (4.4)
Statistics (comparison to Correct)	$t(34)=-0.9$ , <i>ns</i> , $r=0.03$	$t(34)=-1.1$ , <i>ns</i> , $r=0.03$	$t(34)=-1.4$ , <i>ns</i> , $r=0.04$	$t(34)=-1.7$ , <i>ns</i> , $r=0.05$	$t(34)=-1.7$ , <i>ns</i> , $r=0.05$

Physical – Graduate	10.1 (0.7)	12.1 (1.0)	16.0 (1.0)	21.6 (1.8)	29.0 (3.4)
Statistics (comparison to Correct)	$t(28)=1.0$ , <i>ns</i> , $r=0.04$	$t(28)=0.8$ , <i>ns</i> , $r=0.03$	$t(28)=-0.2$ , <i>ns</i> , $r=0.01$	$t(28)=-1.3$ , <i>ns</i> , $r=0.05$	$t(28)=-1.6$ , <i>ns</i> , $r=0.06$

*Note.* <sup>1</sup> The values in bracket represent the standard deviation about the mean. <sup>2</sup> The value indicates the effect size.

**Table A3. Proportion of responses classified as relying on the Correlation Heuristic (CH) in different treatments for different educational backgrounds and levels of education in Chapter 4’s Experiment 1. Comparison statistics with the correct accumulation’s CH value (= 0%) are also shown.**

Treatment	CH (%)	Statistics (comparison to Correct)
Correct	00	-
Graphical – non-STEM	65	$t(22)=6.4$ , $p<.001$ , $r=0.81$ <sup>1</sup>
Graphical – STEM	45	$t(43)=6.0$ , $p<.001$ , $r=0.68$
Physical – non-STEM	08	$t(24)=1.4$ , <i>ns</i> , $r=0.27$
Physical – STEM	08	$t(36)=1.8$ , <i>ns</i> , $r=0.29$
Graphical – Undergraduate	54	$t(36)=6.5$ , $p<.001$ , $r=0.18$
Graphical – Graduate	50	$t(29)=5.4$ , $p<.001$ , $r=0.18$
Physical – Undergraduate	08	$t(34)=1.8$ , <i>ns</i> , $r=0.05$
Physical – Graduate	10	$t(28)=1.4$ , <i>ns</i> , $r=0.05$

*Note.* <sup>1</sup> The value indicates the effect size.

## Appendix B: Effectiveness of Physical Representation in STEM/non-STEM Backgrounds and Graduate/Undergraduate Levels of Education in Chapter 4's Experiment 2

**Table B1. The correct accumulation in different time periods and the corresponding average accumulation in different representations and problems split by education background in Chapter 4's Experiment 2.**

Increasing problem					
Representation and backgrounds	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	20.0 (0.0) <sup>1</sup>	22.0 (0.0)	26.0 (0.0)	32.0 (0.0)	40.0 (0.0)
Graphical – non-STEM	20.0 (0.0)	<b>21.4 (0.5)</b>	<b>23.1 (1.6)</b>	<b>25.1 (3.3)</b>	<b>27.4 (5.9)</b>
Statistics (comparison to Correct)	<i>t</i> (06)=0.0, <i>ns</i> , <i>r</i> =0.00 <sup>2</sup>	<b><i>t</i>(06)=-2.8, <i>p</i> &lt; .05, <i>r</i>=0.75</b>	<b><i>t</i>(06)=-4.8, <i>p</i> &lt; .01, <i>r</i>=0.89</b>	<b><i>t</i>(06)=-5.4, <i>p</i> &lt; .01, <i>r</i>=0.91</b>	<b><i>t</i>(06)=-5.7, <i>p</i> &lt; .001, <i>r</i>=0.92</b>
Graphical – STEM	17.9 (6.3)	19.3 (6.1)	<b>21.5 (6.4)</b>	<b>24.3 (7.6)</b>	<b>27.7 (10.0)</b>
Statistics (comparison to Correct)	<i>t</i> (18)=-1.5, <i>ns</i> , <i>r</i> =0.33	<i>t</i> (18)=-1.9, <i>ns</i> , <i>r</i> =0.41	<b><i>t</i>(18)=-3.1, <i>p</i> &lt; .01, <i>r</i>=0.59</b>	<b><i>t</i>(18)=-4.4, <i>p</i> &lt; .001, <i>r</i>=0.72</b>	<b><i>t</i>(18)=-5.4, <i>p</i> &lt; .001, <i>r</i>=0.79</b>
Text – non-STEM	20.0 (0.0)	<b>21.0 (0.7)</b>	<b>22.2 (1.4)</b>	<b>23.0 (2.1)</b>	<b>24.0 (2.8)</b>
Statistics (comparison to Correct)	<i>t</i> (04)=0.0, <i>ns</i> , <i>r</i> =0.00	<b><i>t</i>(04)=-3.2, <i>p</i> &lt; .05, <i>r</i>=0.85</b>	<b><i>t</i>(04)=-6.3, <i>p</i> &lt; .01, <i>r</i>=0.95</b>	<b><i>t</i>(04)=-9.5, <i>p</i> &lt; .001, <i>r</i>=0.98</b>	<b><i>t</i>(04)=-12.6, <i>p</i> &lt; .001, <i>r</i>=0.99</b>
Text – STEM	18.1 (6.0)	19.8 (5.9)	<b>22.1 (6.2)</b>	<b>25.1 (7.4)</b>	<b>28.8 (9.8)</b>
Statistics (comparison to Correct)	<i>t</i> (20)=-1.5, <i>ns</i> , <i>r</i> =0.32	<i>t</i> (20)=-1.7, <i>ns</i> , <i>r</i> =0.36	<b><i>t</i>(20)=-2.9, <i>p</i> &lt; .01, <i>r</i>=0.54</b>	<b><i>t</i>(20)=-4.3, <i>p</i> &lt; .001, <i>r</i>=0.69</b>	<b><i>t</i>(20)=-5.3, <i>p</i> &lt; .001, <i>r</i>=0.76</b>
Physical – non-STEM	20.0 (0.0)	22.0 (0.0)	25.9 (0.6)	31.5 (1.7)	39.1 (3.3)
Statistics (comparison to Correct)	<i>t</i> (12)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (12)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (12)=-1.0, <i>ns</i> , <i>r</i> =0.28	<i>t</i> (12)=-1.0, <i>ns</i> , <i>r</i> =0.28	<i>t</i> (12)=-1.0, <i>ns</i> , <i>r</i> =0.28
Physical – STEM	20.0 (0.0)	22.0 (0.0)	25.7 (0.8)	31.1 (2.3)	38.2 (4.5)
Statistics (comparison to Correct)	<i>t</i> (12)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (12)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (12)=-1.5, <i>ns</i> , <i>r</i> =0.40	<i>t</i> (12)=-1.5, <i>ns</i> , <i>r</i> =0.40	<i>t</i> (12)=-1.5, <i>ns</i> , <i>r</i> =0.40
Decreasing problem					
Representation and backgrounds	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	28.0 (0.0)	34.0 (0.0)	38.0 (0.0)	40.0 (0.0)	40.0 (0.0)
Graphical – non-STEM	<b>15.7 (7.2)</b>	<b>15.0 (10.1)</b>	<b>14.0 (12.3)</b>	<b>12.7 (14.0)</b>	<b>11.0 (14.7)</b>
Statistics (comparison to Correct)	<b><i>t</i>(05)=-4.2, <i>p</i> &lt; .01, <i>r</i>=0.88</b>	<b><i>t</i>(05)=-4.6, <i>p</i> &lt; .01, <i>r</i>=0.90</b>	<b><i>t</i>(05)=-4.7, <i>p</i> &lt; .01, <i>r</i>=0.90</b>	<b><i>t</i>(05)=-4.8, <i>p</i> &lt; .01, <i>r</i>=0.91</b>	<b><i>t</i>(05)=-4.8, <i>p</i> &lt; .01, <i>r</i>=0.91</b>
Graphical – STEM	<b>20.7 (9.4)</b>	<b>22.7 (13.1)</b>	<b>23.7 (16.0)</b>	<b>23.7 (17.9)</b>	<b>22.7 (18.9)</b>
Statistics (comparison to Correct)	<b><i>t</i>(11)=-2.7, <i>p</i> &lt; .05, <i>r</i>=0.63</b>	<b><i>t</i>(11)=-3.0, <i>p</i> &lt; .05, <i>r</i>=0.67</b>	<b><i>t</i>(11)=-3.1, <i>p</i> &lt; .05, <i>r</i>=0.68</b>	<b><i>t</i>(11)=-3.2, <i>p</i> &lt; .01, <i>r</i>=0.69</b>	<b><i>t</i>(11)=-3.2, <i>p</i> &lt; .01, <i>r</i>=0.69</b>
Text – non-STEM	<b>13.0 (7.3)</b>	<b>12.3 (10.6)</b>	<b>11.3 (13.1)</b>	<b>10.0 (14.7)</b>	<b>8.3 (15.5)</b>
Statistics (comparison to Correct)	<b><i>t</i>(05)=-5.0, <i>p</i> &lt; .001, <i>r</i>=0.99</b>				

Correct)	<i>p</i> <.01, <i>r</i> =0.91				
Text – STEM	<b>20.5 (9.3)</b>	<b>23.0 (13.3)</b>	<b>24.2 (16.1)</b>	<b>24.0 (18.0)</b>	<b>22.5 (18.9)</b>
Statistics (comparison to Correct)	<i>t</i> (11)=-2.8, <i>p</i> <.05, <i>r</i> =0.65	<i>t</i> (11)=-2.9, <i>p</i> <.05, <i>r</i> =0.66	<i>t</i> (11)=-3.0, <i>p</i> <.05, <i>r</i> =0.67	<i>t</i> (11)=-3.1, <i>p</i> <.01, <i>r</i> =0.68	<i>t</i> (11)=-3.2, <i>p</i> <.01, <i>r</i> =0.69
Physical – non-STEM	19.0 (7.3)	20.0 (11.0)	20.5 (13.8)	20.5 (15.9)	20.0 (17.2)
Statistics (comparison to Correct)	<i>t</i> (03)=-2.4, <i>ns</i> , <i>r</i> =0.81	<i>t</i> (03)=-2.5, <i>ns</i> , <i>r</i> =0.82	<i>t</i> (03)=-2.5, <i>ns</i> , <i>r</i> =0.82	<i>t</i> (03)=-2.5, <i>ns</i> , <i>r</i> =0.82	<i>t</i> (03)=-2.3, <i>ns</i> , <i>r</i> =0.80
Physical – STEM	<b>22.9 (8.4)</b>	<b>26.6 (12.2)</b>	<b>28.9 (15.0)</b>	<b>29.7 (16.9)</b>	<b>29.1 (18.9)</b>
Statistics (comparison to Correct)	<i>t</i> (13)=-2.3, <i>p</i> <.05, <i>r</i> =0.54				

Note. <sup>1</sup> The values in bracket represent the standard deviation about the mean. <sup>2</sup> The value indicates the effect size.

**Table B2. The correct accumulation in different time periods and the corresponding average accumulation in different representations and problems split by levels of education in Chapter 4’s Experiment 2.**

Increasing problem					
Representation and level of education	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	20.0 (0.0) <sup>1</sup>	22.0 (0.0)	26.0 (0.0)	32.0 (0.0)	40.0 (0.0)
Graphical – Undergraduate	20.0 (0.0)	<b>21.3 (0.6)</b>	<b>23.1 (1.7)</b>	<b>25.4 (3.7)</b>	<b>28.1 (6.6)</b>
Statistics (comparison to Correct)	<i>t</i> (13)=0.0, <i>ns</i> , <i>r</i> =0.00 <sup>2</sup>	<i>t</i> (13)=-4.4, <i>p</i> <.001, <i>r</i> =0.77	<i>t</i> (13)=-6.3, <i>p</i> <.001, <i>r</i> =0.87	<i>t</i> (13)=-6.6, <i>p</i> <.001, <i>r</i> =0.88	<i>t</i> (13)=-6.7, <i>p</i> <.001, <i>r</i> =0.88
Graphical – Graduate	16.7 (7.8)	18.3 (7.6)	<b>20.5 (7.9)</b>	<b>23.4 (9.1)</b>	<b>27.0 (11.5)</b>
Statistics (comparison to Correct)	<i>t</i> (11)=-1.5, <i>ns</i> , <i>r</i> =0.41	<i>t</i> (11)=-1.7, <i>ns</i> , <i>r</i> =0.46	<i>t</i> (11)=-2.4, <i>p</i> <.05, <i>r</i> =0.59	<i>t</i> (11)=-3.3, <i>p</i> <.01, <i>r</i> =0.71	<i>t</i> (11)=-3.9, <i>p</i> <.01, <i>r</i> =0.76
Text – Undergraduate	20.0 (0.0)	<b>21.5 (0.5)</b>	<b>23.5 (1.8)</b>	<b>26.2 (4.0)</b>	<b>29.4 (7.2)</b>
Statistics (comparison to Correct)	<i>t</i> (16)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (16)=-4.2, <i>p</i> <.001, <i>r</i> =0.72	<i>t</i> (16)=-5.6, <i>p</i> <.001, <i>r</i> =0.81	<i>t</i> (16)=-6.0, <i>p</i> <.001, <i>r</i> =0.83	<i>t</i> (16)=-6.1, <i>p</i> <.001, <i>r</i> =0.84
Text – Graduate	15.6 (8.8)	17.2 (8.7)	<b>19.3 (8.9)</b>	<b>21.9 (9.8)</b>	<b>24.9 (11.6)</b>
Statistics (comparison to Correct)	<i>t</i> (08)=-1.5, <i>ns</i> , <i>r</i> =0.47	<i>t</i> (08)=-1.7, <i>ns</i> , <i>r</i> =0.52	<i>t</i> (08)=-2.3, <i>p</i> <.05, <i>r</i> =0.63	<i>t</i> (08)=-3.1, <i>p</i> <.05, <i>r</i> =0.74	<i>t</i> (08)=-3.9, <i>p</i> <.01, <i>r</i> =0.81
Physical – Undergraduate	20.0 (0.0)	22.0 (0.0)	26.0 (0.0)	32.0 (0.0)	40.0 (0.0)
Statistics (comparison to Correct)	<i>t</i> (13)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (13)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (13)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (13)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (13)=0.0, <i>ns</i> , <i>r</i> =0.00
Physical – Graduate	20.0 (0.0)	22.0 (0.0)	25.5 (0.9)	30.5 (2.7)	37.0 (5.4)
Statistics (comparison to Correct)	<i>t</i> (11)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (11)=0.0, <i>ns</i> , <i>r</i> =0.00	<i>t</i> (11)=-1.9, <i>ns</i> , <i>r</i> =0.50	<i>t</i> (11)=-1.9, <i>ns</i> , <i>r</i> =0.50	<i>t</i> (11)=-1.9, <i>ns</i> , <i>r</i> =0.50
Decreasing problem					

Representation and level of education	Time 1	Time 2	Time 3	Time 4	Time 5
Correct	28.0 (0.0) <sup>1</sup>	34.0 (0.0)	38.0 (0.0)	40.0 (0.0)	40.0 (0.0)
Graphical – Undergraduate	<b>16.5 (7.9)</b>	<b>16.5 (11.4)</b>	<b>16.0 (14.0)</b>	<b>15.0 (15.8)</b>	<b>13.5 (16.7)</b>
Statistics (comparison to Correct)	<i>t</i> (07)=-4.1, <i>p</i> <.01, <i>r</i> =0.51	<i>t</i> (07)=-4.4, <i>p</i> <.01, <i>r</i> =0.53	<i>t</i> (07)=-4.4, <i>p</i> <.01, <i>r</i> =0.53	<i>t</i> (07)=-4.5, <i>p</i> <.01, <i>r</i> =0.54	<i>t</i> (07)=-4.5, <i>p</i> <.01, <i>r</i> =0.54
Graphical – Graduate	<b>21.0 (9.5)</b>	<b>23.0 (13.0)</b>	<b>24.0 (15.9)</b>	<b>24.0 (17.9)</b>	<b>23.0 (18.9)</b>
Statistics (comparison to Correct)	<i>t</i> (09)=-2.5, <i>p</i> <.05, <i>r</i> =0.27	<i>t</i> (09)=-2.7, <i>p</i> <.05, <i>r</i> =0.29	<i>t</i> (09)=-2.8, <i>p</i> <.05, <i>r</i> =0.30	<i>t</i> (09)=-2.8, <i>p</i> <.05, <i>r</i> =0.30	<i>t</i> (09)=-2.8, <i>p</i> <.05, <i>r</i> =0.30
Text – Undergraduate	<b>14.5 (8.3)</b>	<b>14.5 (12.0)</b>	<b>14.0 (14.8)</b>	<b>13.0 (16.7)</b>	<b>11.5 (17.6)</b>
Statistics (comparison to Correct)	<i>t</i> (07)=-4.6, <i>p</i> <.01, <i>r</i> =0.55				
Text – Graduate	<b>20.8 (9.3)</b>	<b>23.4 (13.3)</b>	<b>24.6 (16.1)</b>	<b>24.4 (17.9)</b>	<b>22.8 (18.9)</b>
Statistics (comparison to Correct)	<i>t</i> (09)=-2.4, <i>p</i> <.05, <i>r</i> =0.26	<i>t</i> (09)=-2.4, <i>p</i> <.05, <i>r</i> =0.26	<i>t</i> (09)=-2.6, <i>p</i> <.05, <i>r</i> =0.28	<i>t</i> (09)=-2.8, <i>p</i> <.05, <i>r</i> =0.30	<i>t</i> (09)=-2.9, <i>p</i> <.05, <i>r</i> =0.31
Physical – Undergraduate	25.4 (4.4)	29.7 (7.5)	32.6 (9.7)	34.0 (11.0)	34.0 (11.5)
Statistics (comparison to Correct)	<i>t</i> (06)=-1.5, <i>ns</i> , <i>r</i> =0.24	<i>t</i> (06)=-1.5, <i>ns</i> , <i>r</i> =0.24	<i>t</i> (06)=-1.5, <i>ns</i> , <i>r</i> =0.24	<i>t</i> (06)=-1.4, <i>ns</i> , <i>r</i> =0.23	<i>t</i> (06)=-1.4, <i>ns</i> , <i>r</i> =0.23
Physical – Graduate	<b>19.8 (9.4)</b>	<b>22.2 (13.6)</b>	<b>23.5 (16.7)</b>	<b>23.6 (18.8)</b>	<b>22.7 (19.8)</b>
Statistics (comparison to Correct)	<i>t</i> (10)=-2.9, <i>p</i> <.05, <i>r</i> =0.28				

Note. <sup>1</sup> The values in bracket represent the standard deviation about the mean. <sup>2</sup> The value indicates the effect size.

**Table B3. Proportion of responses classified as relying on Correlation Heuristic (CH) in different representations and problems split by education background and levels of education in Chapter 4’s Experiment 2. Comparison statistics with the correct accumulation’s CH value (= 0%) are also shown.**

Representation and Education	Increasing problem	
	CH (%)	Statistics (comparison to Correct)
Correct	00	-
Graphical – non-STEM	86	<i>t</i> (06)=6.0, <i>p</i> <.001, <i>r</i> =0.93 <sup>1</sup>
Graphical – STEM	68	<i>t</i> (18)=6.2, <i>p</i> <.001, <i>r</i> =0.83
Text – non-STEM	80	<i>t</i> (04)=4.0, <i>p</i> <.05, <i>r</i> =0.89
Text – STEM	67	<i>t</i> (20)=6.3, <i>p</i> <.001, <i>r</i> =0.82
Physical – non-STEM	08	<i>t</i> (12)=1.0, <i>ns</i> , <i>r</i> =0.28
Physical – STEM	15	<i>t</i> (12)=1.5, <i>ns</i> , <i>r</i> =0.40
Graphical – Undergraduate	79	<i>t</i> (13)=6.9, <i>p</i> <.001, <i>r</i> =0.89
Graphical – Graduate	67	<i>t</i> (11)=4.7, <i>p</i> <.001, <i>r</i> =0.82
Text – Undergraduate	71	<i>t</i> (16)=6.2, <i>p</i> <.001, <i>r</i> =0.84
Text – Graduate	67	<i>t</i> (08)=4.0, <i>p</i> <.01, <i>r</i> =0.82
Physical – Undergraduate	00	<i>t</i> (13)=0.0, <i>ns</i> , <i>r</i> =0.00

<b>Decreasing problem</b>		
<b>Treatment</b>	<b>CH (%)</b>	<b>Statistics (comparison to Correct)</b>
Physical – Graduate	25	$t(11)=1.9, ns, r=0.50$
Correct	00	
Graphical – non-STEM	83	$t(05)=5.0, p<.01, r=0.91$
Graphical – STEM	50	$t(11)=3.3, p<.01, r=0.71$
Text – non-STEM	83	$t(05)=5.0, p<.01, r=0.91$
Text – STEM	42	$t(11)=2.8, p<.05, r=0.65$
Physical – non-STEM	50	$t(03)=1.7, ns, r=0.70$
Physical – STEM	29	$t(13)=2.3, p<.05, r=0.54$
Graphical – Undergraduate	75	$t(07)=4.6, p<.01, r=0.55$
Graphical – Graduate	50	$t(09)=3.0, p<.05, r=0.32$
Text – Undergraduate	75	$t(07)=4.6, p<.01, r=0.55$
Text – Graduate	40	$t(09)=2.4, p<.05, r=0.26$
Physical – Undergraduate	14	$t(06)=1.0, ns, r=0.16$
Physical – Graduate	45	$t(10)=2.9, p<.05, r=0.28$

Note. <sup>1</sup> The value indicates the effect size.